Improving Human Performance in Multi-Human Multi-Robot Interaction

by

Jayam Patel

A Thesis

Submitted to the Faculty

of the

WORCESTER POLYTECHNIC INSTITUTE

In partial fulfillment of the requirements for the

Degree of Doctor of Philosophy

in

Robotics Engineering Department

by

December 2020

APPROVED:

Prof. Carlo Pinciroli, Worcester Polytechnic Institute (Advisor)

Prof. Zhi Li, Worcester Polytechnic Institute (Committee Member)

Prof. Lorenzo Sabattini, University of Modena and Reggio Emilia (Committee Member)

Prof. Erin Solovey, Worcester Polytechnic Institute (Committee Member)

Abstract

Multi-robot systems are envisioned to assist humans in complex missions such as interplanetary exploration, ocean restoration, underground mining, and forest firefighting. In these missions, along with robot autonomy, human input is required to supervise the operation of the robots, and assign and prioritize the tasks assigned to the robots. By their very nature, multi-robot systems are complex systems composed of many interacting entities. As such, these systems exceed the typical human attention span, which several studies place between 7±2 entities in laboratory conditions. A natural approach to improving human performance is to relieve the burden of individual operators by conceiving supervisory control schemes in which multiple humans cooperate.

However, with multiple human users in the system, additional challenges arise. These challenges include unbalanced workload, inhomogeneous awareness, and conflict among operators. This limits the performance of the operators, typically measured in terms of workload, situational awareness, and trust in the system.

In my work, I show that the performance of human users can be improved with mixed granularity of control, increased transparency, and human communication. Mixed granularity of control enables an operator to control high-level task goals such as modifying the environment, as well as lower-level goals such as interacting with an individual robot or a group of robots. Increased transparency aids an operator to understand other operators' and robots' actions. Operators communicate directly, through verbal and non-verbal communication, and indirectly, through information transparency, to understand other operators' actions and intentions. The main technological outcomes of my work are a novel mixed-reality interface for proximal interaction and a novel cloud-based interface for remote interaction. These interfaces enable multiple operators to collaborate with multiple robots in local and remote environments. The main scientific outcome of my work is investigating the effects of

mixed granularity of control, information transparency, and human communication on the operators' performance. My experimental evaluation consists of 8 user studies involving a total of 122 participants, in which I analyze operator workload, awareness, trust, and performance.

To my family

Acknowledgements

I would like to express my sincere gratitude to Prof. Carlo Pinciroli for the opportunity to work at Novel Engineering of Swarm Technologies (NEST) Lab. Anything I write here would not be enough to reflect my appreciation and respect for him. Thank you, Carlo, for being the most amazing advisor, mentor, supervisor and teacher. Thank you for all the academic and life lessons. You helped me grow from a student to a researcher, a scientist, a teacher and a good person. Thank you for all the opportunities presenting at events, advising students, and teaching a class along with you. Most of all, thank you for understanding me and for giving me the strength to drive my research.

I would like to thank Prof. Zhi Li, Prof. Erin Solovey and Prof. Lorenzo Sabattini. Thank you, Prof. Li, for always being available when I needed your advice and help. I really appreciate your guidance and our discussions. Thank you, Prof. Solovey and Prof. Sabattini, for your help in strengthening my thesis and making me a better researcher.

I would like to thank Prajankya Sonar, Tyagaraja Ramaswamy and Yicong “Andy” Xu for collaborating and helping build my research. The long critical sessions with you helped steer my research in the right direction. Thank you for all your support.

Next, I would like to thank my peers, my NEST Lab family, in particular Nathalie Majcherczyk, Nishan Srishankar, Josh Bloom, Dominic Cupo and Arsalan Akhter. Thank you for all the long talks, coffee breaks, all-nighters and the great memories.

I would also like to thank Prof. Taskin Padir and RIVeR Lab (Robotics and Intelligent Vehicles Research Laboratory) for the opportunity to do my MS Thesis (2014-16). Thank you Dr. Vinayak Jagtap, Dr. Velin Dimitrov, and Dr. Dimitry Sinyukov for being the most amazing friends and peers at the RIVeR lab.

I would like to thank the six generations of WPI graduate students for being there in the best and worst times. It would be difficult to list all the names and would like to thank my closest, my lifelong friends, Vinayak Jagtap, Nirav Patel, Nandan Banerjee, Rushabh

Lodha, Koushik Balasubramanian, Sahil Kejriwal, Ajay Prabhu, Rahul Krisnan, Lening Li, Saivimal Sridhar, Dhruv Oza, Aniket Shah, and Ayush Shah. Thank you for all the memories of the crazy epic times.

I would like to thank my friends. Thank you Nilay Parikh, Jay Tandel, Vishal Thakker, Vivek Sanandiya, Aakash Barbhaya and Shilen Patel (B.Eng. and family friends), for your support. Nilay, thank you for reading my manuscript and giving me valuable feedback. I appreciate your support and positive thoughts. Thank you Trupal Patel, Shreeraj Shah, Nishant “Chintoo” Patel, and Nishant “Kuki” Patel (childhood friends). It was thanks to you all that I could reach this stage in my life. Trupal, my oldest friend - since 1998, thank you for always being there and supporting me.

I would like to thank my family in USA, Nilesh Dalal (uncle) and Prerana Dalal (aunty). I would also like to thank my cousin, Sejal Patel (cousin). It was thanks to them that moving to the USA did not feel difficult.

I would like to thank Dr. Ronak Shodhan, Namrata Shodhan, Dr. Darshana Thakker and their family. It was Dr. Shodhan who gave me the dream of pursuing my PhD and have always supported my decisions in life. I am extremely lucky to have met him and known him. Thank you Ronak Sir for everything.

I would like to thank Khushboo Vaidya, my life partner. Thank you Boo for being in my life, supporting me and being patient with me. Thank you for everything. Thank you for reading my manuscripts and helping me make them better. You have always helped me be a better version of myself. I could not have done this without you, my love. I can not thank you enough.

My final thanks to my family, Pragna Patel (મમ્મા/mom), Umesh Patel (ડેડી/dad), Shachi Patel (દીદી/sister), Pranav Patel (જીજુ/brother-in-law), Pransh Patel (ચકલી /Pranshu/nephew), Hemant Vaidya (પપ્પા/father-in-law), Jagruti Vaidya (મમ્મી/mother-in-law), and Gargee “Shiva” Vaidya (Shiva/sister-in-law). મમ્મા ડેડી, તમારા વગર આ કૈજ પોસ્સીબલ ના

હોત. હું જેટલું પણ અહીંયા લખીશ એ ઓછું પડશે. I love you two, thank you for everything. દીદી, my role model, I love you and thank you for being an amazing sister. જીજુ, you always have helped me achieve my dreams, thank you. Pranshu, my munchkin, there is not a single day when I don’t miss you. પપ્પા and મમ્મી, thank you for your constant support and love. Shiva, thank you for your love and support.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

We have dreamt of creating a society with robots as a part of our daily life since Isaac Asimov gifted the world a generation-defining sci-fi novel, *I, Robot* [8]. Asimov, with his book, not only inspired robotics research, but also formalized guidelines of human-robot interaction (HRI) [83]. The essence of these guidelines is that robots should assist humans while ensuring the human's safety. The collaboration of humans and robots opens the way to technology that achieves daring, dangerous goals, while limiting, or even eliminating, human harm. This includes accessing natural and man-made disaster zones and exploring the depths of the universe [24, 55, 81, 87, 163, 175, 197]. Robots can enter a region affected by an earthquake or a forest fire to assist the first responders, find survivors, and escort them to safety. The COVID-19 pandemic is providing a compelling case for human-robot collaboration, where the robots assist medical personnel to monitor the patients, administer treatment, and sanitize the environment [247].

The first step towards this dream is to identify the appropriate robots. The robots should be portable to transport, compact to store, and, most importantly, cheap, so we can replace them if required. Humanoid robots and industrial manipulators, despite their sophistication and high performance, are not necessarily the best choice due to their high cost and complexity. On the other hand, small mobile robots are cheap, versatile, and easy to produce. For example, drones are routinely used to perform inspections in disaster recovery [7]. For the same reason, 44 mobile robots have been used for mitigating the effects of 37 disasters between 2001-2012 [165].

However, small mobile robots are typically not sufficiently capable to act in complete autonomy. It took 20 years to get an iRobot's Roomba from concept to commercialization [1]. It took iRobot 10 more years to make Roomba smart enough for use in most households, which includes autonomous navigation, visual localization, and automated dirt disposal. And that is the best we can get today in a safe, but unstructured environment such as a home. Roomba still relies on human inputs to define regions to avoid and regions to access. Similarly, with autonomous vehicles, we are years away from placing human life at the perils of autonomy. Uber's autonomous test vehicle was involved in 38 crashes until 2018 [210]. In short, a human presence, local or remote, is essential to ensure that robots operate safely and correctly.

A key problem is that, during challenging missions, a human operator might be overburdened due to the amount of information coming from the robots. The robots constantly send individual information about their position, task, and live updates on the mission. An operator needs to understand all the relevant information and interact with the robots. An operator may choose to interact with different granularity of control; control an individual robot or multiple robots, or indirectly influence the robot behaviour by indicating high-level goals, such as "move this obstacle out of the way". An operator may interact with an individual robot to indicate a region of interest without affecting the rest of the robots. Alternatively, an operator may interact with all the robots as a single entity to relocate them to a different region of interest. At a higher level of granularity, an operator may interact with a virtual representation of the environment to assign the robots task such as debris removal or transporting a disaster survivor to safety. Multi-robot systems are complex, and their behavior will often exceed the span of apprehension of any individual operator. The span of apprehension is the number of entities a human can attend to simultaneously. Miller [160] states that for any individual this span is limited to 7 ± 2 entities beyond which the operator's performance is affected negatively.

A natural approach to improving human performance is to relieve the burden of individual operators by involving multiple operators. However, with multiple human operators in the system, additional challenges arise, such as coping with task organization and operator engagement [35, 158], inhomogeneous awareness [130, 180, 193], and ineffective group dynamics [4]. In a more general sense, these challenges exists in every system that involves over one human present *in-the-loop*. These challenges are studied in various domains of research, extending from literature on social psychology [12, 78] to the literature on supervisory control of multi-agent systems [18, 76, 217]. The properties of multi-agent system interrelates with the properties of multi-robot systems, yet lacks the physical aspects of a robot that can influence and manipulate the physical environment. Hence, the studies of these challenges are not directly applicable to a multi-robot system.

As a part of task organization involving a multi-robot system, an operator may control a single robot, multiple robots, influence the environment, or adopt a mixed-granularity approach to control all aspects of the robots. With separate task responsibilities, there could be an imbalance in task load. For example, consider a case in which an operator is responsible to coordinate debris removal, and another is responsible to coordinate safe transport of victims. The first task might be time-consuming and detailed, and during its execution the other operator might be idle waiting for its completion. Additionally, every operator must be equally aware of the robots and the actions that other operators are taking to collaborate and avoid contradicting or negating each other's actions. This may happen when both operators have control over the same group of robots. To avoid such issues, the operators need to communicate their intentions while being aware of each other's actions.

Operators can interact verbally to clarify their intentions and actions, but to interact with robots, the operators require an interface. This interface must be both computationally powerful and easily accessible by the operators. A smart phone or a tablet fits these requirements [241]. Average smart phones or tablets have sufficient hardware to integrate virtual information with real-world objects such as robots and their obstacles. Particularly for first responders, using a smart phone removes the need to physically carry an additional sophisticated interface that can be heavy, may take additional time to set up, and waste critical time. Operators with such interface may like to add virtual entities for robots to interact with, creating a "mixed reality" [16]. With mixed-reality interfaces, operators can create virtual walls and visualize the robot's information, while interacting with both virtual and real entities. Despite these capabilities, mixed reality limits an operator to local interaction and cannot be used in a remote environment. Operators may wish to interact with robots without being physically present in the same environment. This creates a demand for an interface that operators can remotely access. A cloud-based interface serves to this need [226]. With a cloud-based interface, an operator can remotely monitor the task, interact with robots, and influence the outcome without putting human lives in danger. For example, medical personnel can remotely monitor and treat COVID-19 patients without risk of contagion.

In this thesis, I present the design of a mixed-reality interface and a cloud-based interface to enable multiple human operators to interact with multiple robots. I study and report my findings about the impact of mixed granularity of control, increased transparency, and human communication on an operator's performance while engaging in proximal and remote interactions.

1.1 Thesis Structure and Research Contributions

This manuscript is structured as follows.

In Chapter 2, I discuss the state-of-the-art in the design of interaction modalities for multiple operators and multiple robots.

In Chapter 3, I present a mixed-reality interface for a single operator controlling multiple robots that combines two modalities of interaction: environment-oriented and robot-oriented. The environment-oriented modality allows the operator to modify a virtual representation of the environment to indicate a high-level goal for the robots. The robot-oriented modality makes it possible to select individual robots and assign them tasks to increase performance or remedy failures. The work in this chapter was published in:

- J. Patel, Y. Xu, and C. Pinciroli, "Mixed-Granularity Human-Swarm Interaction," 2019 International Conference on Robotics and Automation (ICRA), Montreal, QC, Canada, 2019, pp. 1059-1065, doi: 10.1109/ICRA.2019.8793261.

In Chapter 4, I study the impact of mixed granularity of control with multiple human operators interacting with multiple robots. In particular, I focus on the challenge of an operator going *out-of-the-loop* because of a lack of engagement in the task, awareness of its state, and trust in the system and in the other operators. The work in this chapter was published in:

- J. Patel and C. Pinciroli, "Improving Human Performance Using Mixed Granularity of Control in Multi-Human Multi-Robot Interaction," 2020 The IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN) , Naples, Italy, 2020.

In Chapter 5, I explore the design space of user interfaces to investigate the impact of information transparency on multiple human operators' performance, interaction, situational awareness, workload, and trust. Transparency is a key factor in improving the performance of human-robot interaction. When multi-robot systems are involved, transparency is an even greater challenge, due to the larger number of variables affecting the behavior of the robots as a whole. The work in this chapter was submitted to:

- J. Patel, T. Ramaswamy, Z. Li, and C. Pinciroli, "Transparency in Multi-Human Multi-Robot Interaction," The IEEE Robotics and Automation Letters (RA-L).

In Chapter 6, I study the impact of different communication modes on operator's awareness, workload, trust, and usability in a multi-human multi-robot system. Communication is the key essence for an effective teamwork, be it between humans or be it between humans and robots. Humans can either engage directly through verbal communication or indirectly representing their actions and intentions by using technology or with a mix of both. The work in this chapter was submitted to:

- J. Patel, T. Ramaswamy, Z. Li, and C. Pinciroli, "Direct and Indirect Human Communication in Multi-Human Multi-Robot Interaction," The IEEE Transactions on Human-Machine Systems (THMS).

In Chapter 7, I present a cloud-based interface for multi-human multi-robot remote interaction mimicking the features of the mixed-reality interface. This interface was used to compare the impact of information transparency and human communication in proximal and remote interaction. In addition to investigating the interface usability in an ideal condition, I study the impact of information loss on the performance, situational awareness, workload and trust of the operator in a multi-human multi-robot remote interaction. Information loss in a remote interaction occurs due to limitations in the network's bandwidth, hardware limitations, and physical distance between the operators and the robots. The work in this chapter was submitted to:

- J. Patel, P. Sonar, and C. Pinciroli, "On Multi-Human Multi-Robot Remote Interaction: A Study of Transparency, Inter-Human Communication and Information Loss in Remote Interaction," Springer Journal of Swarm Intelligence.

In Chapter 8, I conclude my thesis and discuss possible developments of this work for further research.

Chapter 2

State of the Art

Humans have envisioned interacting with robots since Nikola Tesla demonstrated a radio-controlled boat, laying a foundation to the field of human-robot interaction (HRI) [173]. Since then, HRI research has focused on identifying suitable human interfaces and investigating methods to make these interfaces more usable.

According to Sholtz et al. [203], the role of a human can be categorized into five types; *supervisor, operator, teammate, mechanic* or *bystander*. As a *supervisor*, a human monitors the robots and the overall situation. The supervisor evaluates the situation and the goal of the robots. This includes monitoring autonomous robots that do not rely on the human for taking decisions, for e.g., a domestic robot vacuum. As an *operator*, unlike the supervisor, the human controls the robot to meet the identified goals. This includes tele-operated robotic arm for medical surgery. As a *teammate*, a human directly collaborates with the robot on the task at hand. This includes co-bots, collaborative robots, where human and robot share a common goal but have their individual responsibilities, for e.g., a human and a robot team for industrial assembly. As a *mechanic*, a human troubleshoots and fixes hardware or software issues in the robots. These issues may include battery faults, software faults, or motor failures. As a *bystander*, a human does not interact with the robots, but is just another entity in the environment for the robots to work around, e.g., pedestrians for autonomous vehicles.

These roles neither comprise the capability of a human to learn from a robot nor a robot to learn from a human. For this reason, Goodrich et al. [83] added two more roles, the role of a *mentor* and of an *information user*. As a *mentor*, a human can teach robot a new behavior, which includes a robot learning from a human demonstration. As an *information user*, a human can learn for the information collected by the robot, for e.g., military personnel using information collected by a robot responsible for reconnaissance missions.

Although there are various roles a human can play in the interaction, the common desire with each role is to enhance the performance of the system. We can measure human performance in quantitative and subjective scales [164, 215]. Quantitative scales can include success measured in time taken to complete a task and stress measured in heart rate elevation [227]. Subjective scales can include questionnaires to quantify system usability and reliability [13, 201, 224, 236]. In both types of scales, human performance is influenced by three factors: situational awareness, workload, and trust in the robots [35, 65, 100]. Situational awareness is "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future" [66, 111]. Situational awareness of a system with robots may include a visual representation of the robots, their position, their current actions and their future plans. Workload is "the intended demands of a task created by its objectives, duration and structure and by the human and system resources provided" [89]. Trust is "the attitude that an agent will help achieve an individual's goal in a situation characterized by uncertainty and vulnerability" [131].

These factors, individually or in combination, may affect the human performance based on the role the human plays in the interaction. For example, for a mentor or a teammate, the final outcome of the robot's task is more significant for the human performance, influencing the human's trust in the robots. Likewise, the performance of a supervisor or an information user may be related to the information provided by the robots, affecting the human's workload and situational awareness. Similarly, for an operator or a mechanic, the outcome depends on the human's direct interaction with the robots while being aware of the task demands, affecting the human's trust, workload and situational awareness.

Typically, the operator is the most demanding role, especially when interacting with multiple robots. The operator has to be actively aware of the situation, control and monitor all the robots while planning their future actions. Endsley et al. [65] address this challenge and indicates the granularity of control as a key aspect affecting the performance of the operator. Granularity of control is the level of control with which a human operator can interact with the robots. We can categorize the granularity of control into: robot-oriented, multi-robot oriented, and environment oriented. Robot-oriented interaction is a level of control in which an operator may interact with an individual robot from a group of robots. This kind of interaction includes controlling a robot with continuous input or specifying a desired position for the robot. Multi-robot-oriented interaction is a level of control in which an operator may interact with multiple robots as a single entity. This kind of interaction includes simultaneous navigation of all the robots to a region of interest. Environment-oriented interaction is a level of control in which an operator may modify the environment virtually or physically to influence the behaviour of the robots. This kind of interaction includes adding virtual beacon-based influence and specifying a goal of an object for the robot to transport.

2.1 Robot-Oriented Interaction

In robot-oriented modality, the operator should be able to control a robot and manipulate its position. The literature on this modality includes different interfaces that enable an operator to use this modality. Setter et al. [208] propose to use a haptic interface to control a *leader* robot. The operator, in this work, can manipulate the position of the leader and expect other robots to follow. The operator experiences a haptic force corresponding to the direction of the motion. Weaker haptic forces correspond to the directions in which the robots can follow, while stronger haptic forces correspond to the direction that robots should avoid. In this work, the leader attracts other robots and their behaviour compels them to follow the leader, like fish in a school follow their leader. In contrast, Goodrich et al. [82] demonstrate a haptic interface to control a predator that other robots will avoid, inspired by how fish avoids a shark. Using this interface, an operator can control the *predator* robot to avoid collisions with other robots. The concept of leader-based and predator-based control definitely reduces the cognitive workload of an operator, but the interface breaks if the leader or the predator encounter a failure. The interface cannot elect or select a leader or a predator during such events.

To overcome this issue, Kapelmann-Zafra et al. [113] discuss a graphic user interface (GUI) that allows an operator to select a robot at random. The operator can then manipulate the randomly selected robot as needed. The operator can also request to switch access to another robot. However, random selection, an operator may waste time waiting for the selection of the robot they want to re-position to a region of interest. This might cause an operator to experience frustration. Cacace et al. [25] offer a solution to this problem. Instead of choosing a robot at random, they propose an algorithm to select a robot for the operator to manipulate. This selected robot is in proximity of the region of interest and would restrict an operator to cycle through the set of robots, saving the operator's time and improving cognitive load.

Nagi et al. [168–170] explores computer vision-based interaction that enables an operator to select robots. Using a colored glove, the operator can create hand-gestures to send commands to the robots. In this work, the robots can detect the gesture information from their point of view and collectively understand the intention of the operator. The success of gesture detection depends on the point of view of the robots. To avoid this issue, Alonso-Mora et al. [5] present a centralized gesture recognition platform based on the Microsoft Kinect [88]. In this work, the operator can point and select a robot of their choice. The operator then can manipulate the robots at their will. Similar to this work, Lee et al. [134] propose a joystick-based interface that enables an operator to tele-operate the robots. The operator can select a robot of their choice and pinpoint a location for the robots to reach. This allows an operator to select a robot of their choice.

In these works of robot-oriented modality, the operator is limited to only one kind of interface, thereby limiting the means to interact with the robots. Gromov et al. [85] reports a multi-modal interface for an operator to use. This multi-modal interface is a fusion of a bio-sensor (electromyography sensors), a natural language processor, and computer vision techniques to enable an operator to control robots with an input of their choice. The operator can control robots either by pointing at them, or instruct them with a vocal command. The multi-modality feature enables an operator to choose a method of their liking to interact with the robots.

A common issue in platforms that only offer robot-oriented interaction is that the operator can control only one robot and the large of number of robots can cause an operator to reach the limits of their cognitive capabilities [136, 140]. The operator will have to identify the robot to select, understand that robot, control it and then transfer attention to the next robot. The operator's awareness will be limited to the interaction with an individual robot and not the multi-robot system, affecting the performance of the operator.

Hence, even though the robot-oriented modality enables an operator to control individual robots, it is not be a suitable modality to interact with numerous robots.

2.2 Multi-Robot-Oriented Interaction

In contrast to the robot-oriented modality, the multi-robot-oriented modality allows an operator to interact with all the robots as a common entity. This includes engaging in collective manipulation and moving the robots as a single entity. Podevijn et al. [187] devised an interaction interface in which the operator moves their body to control the robots as a single entity. This interface also gives the operator the ability of splitting robots into groups and merging them back. The operator, however, does not not have the ability to select a subset of robots. Chen at al. [41] extends gesture control by enabling the operator to manually select a group of robots and move them as a single entity. In this work, the operator can draw a shape to select all the robots enclosed in that shape. This feature grants the operator flexibility in selecting a subset of robots and maneuver them at will. In these works, the accuracy of the navigation depends on the gesture recognition system and lacks a feedback mechanism to improve the human performance. To tackle this issue, Lee et al. [129] and Hong et al. [97] take advantage of haptic technology for collective manipulation. The robots in these approaches navigate while maintaining a formation. The operator is responsible for controlling the centroid of this formation to manipulate the robots as a single entity. With haptic feedback, not only accuracy of collective manipulation is improved but also positively impacts the usability of the system.

Despite of the benefits of collective manipulation, the operator has to constantly interact with the robots and ensure that the robots do not collide with each other or with other entities in the environment. This collision can cause damage to the robot's hardware and sensors, affecting the robot's performance. The constant controlling and monitoring of the robots can negatively affect the operator's cognitive workload. Hence, as a part of multi-robot-oriented modality, the operator should be allowed to specify a final destination or provide way-points for robots to follow to reach to the final destination. Ayanian et al. [9] proposes one such method. In this work, the operator, using a touchscreen tablet, can define bounding boxes as way-points for robots to navigate in a cluttered environment. The robots then navigate through these way-points and manipulating around obstacles in the environment. Diaz-Mercado et al. [57] extends this approach by specifying a shape as a destination for robots. The operator, in this approach, can draw a shape on a touchscreen tablet and the robots distribute themselves to form the shape. The key contribution of this work is the density-based distribution algorithm using which the robots generate a destination for each robot to form the operator specified shape. The advantage of these works, i.e., multi-robot-oriented modality, is that a limited number of inputs are required to manipulate numerous robots. However, the downside of this modality is the lack of fine-grained control of robots. The operator is lacking the capability of performing corrective maneuvers with a single robot and cannot address their individual failures.

2.3 Environment-Oriented Interaction

Finally, the environment-oriented modality enables an operator to influence the robots by modifying the physical or the virtual environment. Jang et al. [104] reports an interface that enables an operator to create virtual walls. The robots then interpret these virtual walls as obstacles and regions to avoid while navigating in the environment. Bashyal et al. [14] take this a step further. In their work, the operator can place beacons in the environment. The operator defines whether these beacons act as attractors or repulsors. The robots treat the attracting beacons as house flies interpret a light source. The repeller beacons represent danger zones for the robots to avoid.

Beyond adding elements to the environment, the operator should also be able to change the positions of the objects in the environment to convey their intent of transporting an object. The robots then should be able to move the object according to the operator's request. This high-level kind of interaction lowers the cognitive load experienced by the operator. However, similar to the multi-robot-oriented modality, this modality lacks the fine-grained control for the operator to perform corrective maneuvers with a single robot.

A possible solution to this issue, would be to allow an operator to have control over robots using multiple control modalities. The operator can convey their intent using environment-oriented interaction, simultaneously control all robots using multi-robot-oriented interaction, and perform fine-grained control using robot-oriented interaction. Kolling et al. [123] came closest to this approach of mixed granularity of control. The authors compare robot-oriented modality and environment-oriented modality. The operators were tasked with exploring the environment and could place attractor beacons or control individual robots. However, in their approach, the operator was incapable of using two or more modalities in the same task. The operator being capable of using multiple granulaties could have influenced the results. Hence, in my thesis, I investigate the impact of multiple control granularities on an operator's performance.

2.4 Information Transparency

After control of multiple robots comes the problem of understanding them, i.e., making the robots more transparent and legible. Transparency is a key property of any type of interaction. In a transparent interaction, the operator is aware of the robots' current states and actions while being able to predict their future actions. Significant effort has been dedicated to making the robots understandable and transparent. The concept of anthropomorphism is a product of this research [13, 61]. A human can better understand an entity that they can physically relate to, including humanoid robots and industrial manipulators. However, the challenge is different when it comes to mobile robots. The mobile robots lack human-like characteristics for operators to relate to and understand. Knight et al. [121] attempts to study this problem with a single robot moving in predetermined patterns. In their study, the bystanders were asked about their understanding of the mobile robot's movements. They report that the bystanders were trying to make sense of the robot behaviour, but could not identify, the rationale for the robot's behavior. For example, in one task a robot moved in a straight line for a few time steps and then moved in a sine wave pattern. The bystanders reported the robot knew at first what it wanted to do, but then it faced an error and started moving in random directions. This study, although limited to one robot's movement, proved that understanding a mobile robot is difficult and a research problem in itself.

Capelli et al. [29] reports the results of a user study to investigate the challenge of legibility with multiple robots. In this work, the authors test their approach with multiple robots in a navigation task. These robots are color-coded and divided in three sets. Each set of robots much navigate to their respective goals. The study reported that the motion of multiple robots is legible and is significantly impacted by the trajectory taken while navigating to the goal position. In contrast to this work, Ghiringhelli et al. [79] presents an augment-reality based approach to graphically represent the robots' states and actions. The paper focuses on the technological aspect of the interface rather than on the usability aspect. Chen et al. [40] and Mercado et al. [159] report user studies to report a positive impact of robot transparency on an operator's situational awareness, trust and workload. These studies are performed with simulated point-mass models of the robots which lack physical properties of mobile robots, creating a gap between results collected with simulated environment and the results collected with physical environment: *the reality gap* [103].

2.5 Multi-Human Interaction

The problem of controlling and understanding multiple robots is a significant challenge, and the challenge further escalates when multiple operators wish to interact with the robots. When multiple operators control the same robot, conflicts might arise. The individual robot can either consider only the latest input and disregard all previous inputs, or can use a shared-control mechanism to couple the inputs of two operators. Feth et al. [71] demonstrate a haptic force-based shared-control approach for a tele-operated robot. The haptic device creates a resistance depending on the operators' inputs to avoid conflicts of robot manipulation in opposite directions. However, this approach is specific to manipulators and is not applicable to mobile robots.

With multiple operators interacting with multiple robots, Schauß et al. [202] reports a coupling-based approach for two operators controlling two manipulators. In this work, the operators are assigned their respective manipulator and cannot control the other manipulator, making conflicts impossible. In the domain of multiple mobile robots, You et al. [245] reports a user study with two operators controlling their respective robots for manually pushing physical objects from one place to another. They divided the task environment into two regions, with a operator-robot pair assigned to each region and limited the operator from moving from one region to another. Due to this assumption, the study could not comment on conflicts between operators. In contrast, Lee et al. [132] compares the performance of operators while controlling robots from a shared pool of robots with an assigned pool of robots. The operators can engage with robots using robot-oriented modality and can manipulate one robot at a time. Their findings show that the performance of the operators is better when they can manipulate robots from the assigned pool. Their performance drops when they control robots from the shared pool. This indicates that the operators can negate each other's actions while sharing control of robots. Lewis et al. [139] extend this work to investigate the impact of team organization on the operators' performance. The authors compared three forms of team organization; joint control where both operators had full authority over the robots, mixed control where one operator acts as an assistant to another operator, and split control where both operators had their own sub-team to control. Their study concludes the joint control strategy as the best form of team organization while engaged in a search mission for simulated victims. Lewis et al. [137] furthers this research to study the impact of situational awareness of an operator while controlling individual robots. The authors compare the reported awareness of operators when the robots are manually controlled with robots performing autonomous exploration. Their study reports that operators have a better awareness when they are manually controlling the robots as compared to when the robots are autonomously navigating in the environment. This indicates that the operators are more *in-the-loop* and engaged in the task while using robot-oriented modality.

These studies, however, are limited to robot-oriented modality and do not consider the possibility of engaging multiple operators or improving their performance with mixed granularity control of multiple robots.

Hence, in my thesis, I present my approach of allowing multiple operators to use mixed granularity of control over multiple robots. The main technological outcomes of my work are a novel mixed reality interface for proximal interaction and a novel cloud-based interface for remote interaction. These interfaces enable multiple operators to collaborate with multiple robots in local and remote environments. The main scientific outcome of my work is investigating the effects of mixed granularity of control, information transparency, and human communication on the operators' performance. My experimental evaluation consists of 8 user studies involving a total of 154 participants, in which I analyze operator workload, awareness, trust, and performance.

Chapter 3

Mixed Granularity of Control

In multi-robot systems for humanitarian missions, robot autonomy covers only a part of the picture. An equally important aspect of the technology is that the humans must be able to interface with the robots to issue commands and affect the way these commands are executed during the mission [123].

Despite the importance of the human factor, effective interfaces to interact with robots are currently at their early stages. From a UI/UX standpoint, an interface is effective when (i) it offers a coherent mental model of the system and its purpose and (ii) when the available interactions match this mental model [174]. A classical example is the design of windows-based point-and-click interfaces.

Problems (i) and (ii) constitute a considerable hurdle in the design of interfaces for human multi-robot interaction. Analogously to the problem of designing multi-robot algorithms, in human multi-robot interaction, a fundamental aspect is the way an operator *thinks* a multi-robot system [123]. Broadly speaking, the three primary mental models that have been employed are robot-oriented (i.e., the multi-robot system as a collection of individual robots), multi-robot-oriented (i.e., the multi-robot system as a coherent unit), and environment-oriented (i.e., modify the environment to specify a goal).

In this chapter, I argue that neither approach, alone, is adequate to engage with robots in an effective way when complex missions must be completed. I argue, instead, that the correct abstraction level must be mixed, and include (at least) an environment-oriented aspect and a robot-oriented aspect. Through environment-oriented primitives, the operator can specify high-level goals without directly engaging with the robots. For example, in a collective transport scenario, the operator should dictate where the objects should be moved, rather than assigning tasks to the robots directly. However, at the same time, I recognize that the ability to engage with individual robots can be critical to improve performance. In case of robot failures, for example, a human operator with a global view of the system could be more effective than the robots itself in reassigning healthy robots to new tasks.

The main contribution of this chapter is the first human multi-robot interface that enables operators to both specify high-level goals and to affect the behavior of individual robots during the mission. For this chapter, I focused on an inherently collaborative task composed of several phases: collective transport. Using a tablet-based reality application, the operator can select the objects to transport and drag them to their intended destination. The robots then autonomously allocates robots to the task and completes it. During execution, the operator can also select individual robots to reassign them to new transport tasks or to replace failed units.

The chapter is organized as follows. In Sec. 3.1 I discuss related work on human multi-robot interfaces. In Sec. 3.2 I present the system and its design. In Sec. 3.3 I report the experimental evaluation, which includes unit tests for the behaviors and a user study on the usability of the application. The chapter is summarized in Sec. 3.4.

3.1 Related Work on Granularity of Control

In reviewing relevant literature, two aspects are prominent: the *level of granularity* offered by a specific human multi-robot interface, and the *type of tasks* the interface most naturally enables. Regarding the level of granularity, I identify three possible alternatives: *robot-oriented*, *multi-robot-oriented*, and *environment-oriented*.

Robot-oriented interactions occur when an operator must engage with individual robots, e.g., to make them into leaders other robots must follow [208], to hand-pick robots for a specific task [5, 30, 73, 85, 113, 169, 187], or to use a robot as tangible interface for gaming and education [128, 178]. The main advantage of these interfaces is the simplicity of their abstraction (the operator becomes part of the multi-robot system); however, with collective behaviors in which the operator must interact with multiple robots, the downside of this approach is the large amount of information an operator must provide to the robots (e.g., in the form of number of operator commands per task).

At the opposite side of the spectrum, multi-robot-oriented interactions occur when an operator treats a robot in the multi-robot system as a unique entity [41, 96, 129]. This modality of interaction has been demonstrated in navigation tasks, e.g., beacon-based [14], population density-based [57], and waypoint-based [9]. The main advantage of swarm-based interaction is that a small number of commands, e.g., the target position, is sufficient to control a large robot swarm. The price to pay, however, is the lack of fine-grained control on the robots. This makes it impossible to deal with suboptimal task assignment, individual failures, and error cascades.

Finally, *environment-oriented* interactions occur when the operator does not interact directly with the robots, but rather performs an environmental modification, either in the real world or in a virtual environment, that the robots interprets as a new task to perform. Possible examples of this type of interaction include object clustering and sorting,

Figure 3.1: System overview with a single human operator.

construction, shape formation, and self-assembly of modular structures. The advantage of this modality is that the mental model the operator must acquire is very intuitive (describe what you want, rather than how to achieve it) and it is likely to produce concise sets of commands. However, the main disadvantage of environment-oriented interactions is lack of fine-grained control, analogously to what I discussed for multi-robot-oriented interaction.

Kolling *et al.* [122] performed a study that is central to the topic of this chapter. They compared two modalities of controlling a robot swarm, namely robot-oriented and environment-oriented, in a task in which the robots had to diffuse in the environment while avoiding connectivity loss. The robots performed a simple form of foraging, and could be controlled either by direct commands, or by placing attractive beacons in the environment. The conclusions of this study are that environment-oriented interactions are not as effective as robot-oriented interactions, especially when environments are cluttered and many robots are involved.

In this chapter, I seek to investigate whether these conclusions depend on the nature of the task (foraging vs. collective transport) and whether combining, rather than comparing, environment-oriented and robot-oriented interactions can produce more effective interfaces.

3.2 Mixed Reality-Based Interaction Interface

The purpose of this chapter is to create an intuitive interface to allow an operator to interact with a team of robots at two levels: the goal and the individual robots. Through the interface, the operator should be able to create multi-robot-oriented goals, affect the behavior of individual robots, and monitor the progress of the robots.

To highlight the collaborative aspect of the task that the robots must accomplish, I opted to focus on a specific scenario - collective transport. Collective transport entails several phases: assignment of robots to the task, approaching the object, navigating, and performing correcting maneuvers when necessary. Hence, I consider it a suitable testbed for a mixed granularity interface.

3.2.1 System Overview

The system (a diagram of which is reported in Fig. 3.1) comprises four components:

1. A mixed reality interface implemented as an app for a hand-held device;

2. A team of robots performing collective transport;

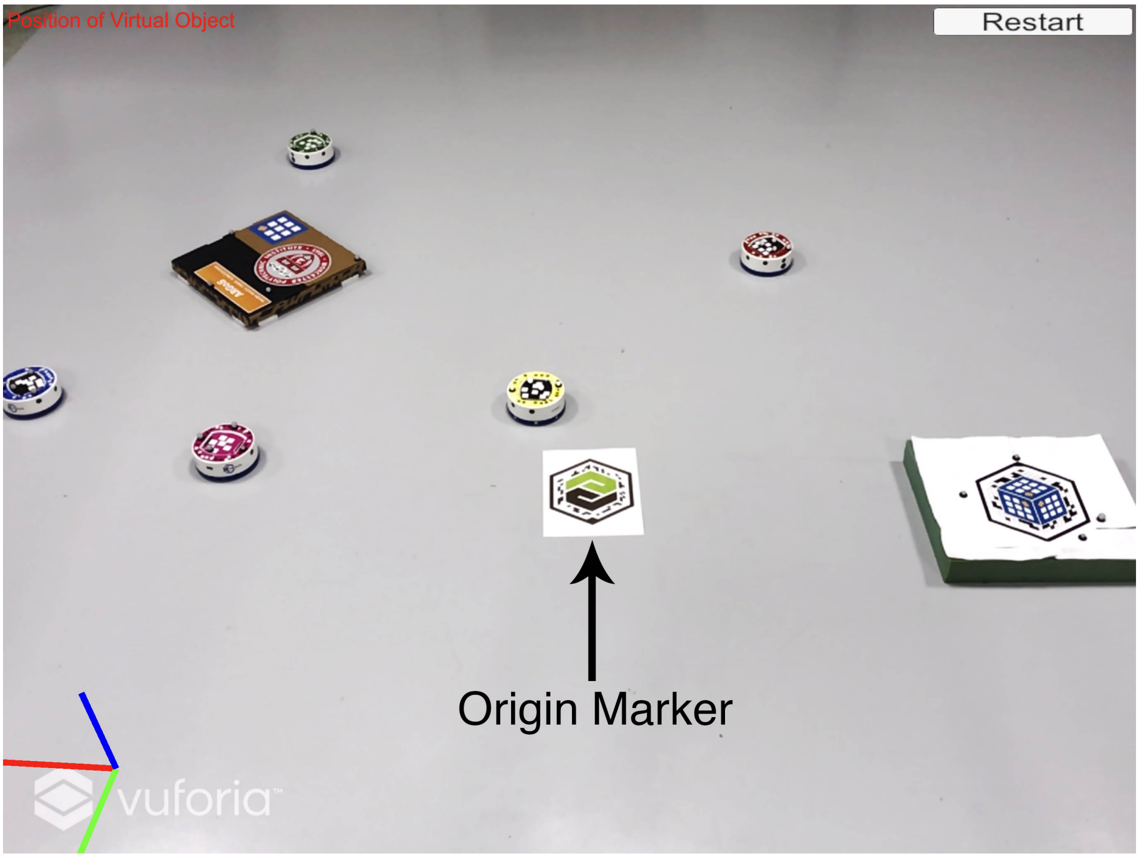


Figure 3.2: Screenshot of the MR Interface running on an iPad. The overlaid black arrow indicates the origin marker for initializing the coordinate frame of the interface.

3. A 10-camera VICON motion tracking system, which monitors the position of the robots and of the objects being transported; and

4. ARGoS [186], a multi-robot simulator that I modified to act as a software glue for the overall system.

The information flow starts at the hand-held device, when the operator defines a new transport goal or designates a new position for a robot. The command is then transmitted to ARGoS, which processes it and generates high-level motion goals for the robots. ARGoS communicates the motion goals to the robots, and the latter execute the goals.

To make this information flow possible through ARGoS, I realized a series of extensions. The most important is a new type of physics engine that, instead of calculating values from a numerical model, uses the positional information generated by the motion tracking system. In this context, ARGoS ceases to be a simulator and it becomes a middleware.[1]

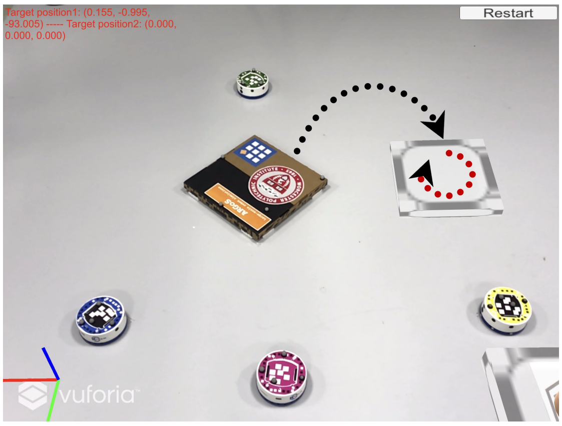
3.2.2 Mixed Reality Interface

Human Multi-Robot Interaction App. The interaction between the operator and the robot happens through the reality (MR) application installed on an iOS 9+ hand-held device. The application can recognize objects and robots. Once recognized, the app overlays a physical entity (robot or object) with a virtual object. The operator can specify the desired translation and rotation of the physical object by manipulating its virtual counterpart. A virtual object is translated using a one-finger swipe and rotated using a two-finger twist gesture. The manipulation of a virtual object happens in three touch phases; *start*, *move*, and *end*. At the start of the touch phase, the app selects the virtual object intersecting with the touch point. The move phase records the motion gestures input by the operator. In the end phase, the app sends the final pose of the virtual object to ARGoS. Fig. 3.2 shows the screenshot of the MR application. The top-left corner of the application displays the desired goal position; the bottom-left corner displays the current reference frame based on the location of the device with respect to the origin marker. The origin marker can be any image, as long as the app can uniquely identify it.

Mixed Reality Engine. To realize the app I employed Vuforia [2], a well-known software development kit for reality applications. Vuforia uses fiducial markers for recognition and tracking of physical objects in real time. Vuforia provides simultaneous tracking of 5 image targets and 2 object targets. Vuforia can track a 0.2 m-wide target from a distance of 2 m, but the actual readings may vary based on light conditions, camera resolution, camera focus, and features of the fiducial marker. To develop the app, I integrated Vuforia with the Unity Game Engine, which natively supports several hand-held devices.

[1] A video demonstration of the system is available at https://youtu.be/kSkxtg5YOS4.

(a) Object recognition



(b) New goal defined

(c) Robots approach and push

(d) Transport complete

Figure 3.3: Object goal manipulation by interacting with the virtual object through the interface. The overlaid dotted black arrow indicates the one-finger swipe gesture used to move the virtual object and the overlaid red dotted arrow indicates the two-finger rotation gesture.

3.2.3 Control Granularity

Object Goal Manipulation. As explained, when the app recognizes an object, it overlays a virtual object over it. This virtual object can be manipulated to generate the desired goal pose for the physical object. Multiple objects can be manipulated through this gesture and the respective robots can transport the objects in parallel. If all robots are busy transporting other objects, the app queues the request and waits for the completion of ongoing tasks. Fig. 3.3a shows a detected object overlaid with a virtual object. Fig. 3.3b illustrates the

(a) Robot recognition

(b) New robot position

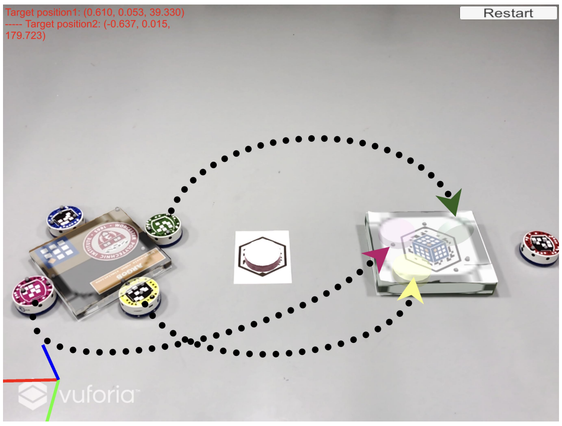
(c) Robots re-positioned

Figure 3.4: Robot manipulation by interacting with the virtual robots through the interface. The overlaid dotted black arrow indicates the one-finger swipe gesture to move the virtual object and the arrowhead color indicates the moved virtual robots.

manipulation of the virtual object.

Robot Manipulation. When the app recognizes a robot, it overlays a virtual colored marker over it. The color of the virtual marker resembles the color of the physical markers glued to the corresponding robot. Once the operator gestures a new pose, other robots belonging to the same robot-team as the selected robot freeze until the latter achieves its new pose. During freeze time, multiple robots can be manipulated in parallel. Fig. 3.4a shows the identified robots with virtual markers overlaid. Fig. 3.4b shows the manipulation of a virtual marker that encodes the new robot pose.

(a) Two object tasks



(b) Team reassignment gesture

(c) Robots rearrange

(d) Team reassigned

Figure 3.5: Team reassignment through the interface to complete the task of moving object. The overlaid dotted black arrow indicates the one-finger swipe gesture to move the virtual object and the red dotted arrow indicates the two-finger rotation gesture.

Team Reassignment. The virtual robots can be selected, moved, and overlapped with the virtual objects to reassign them to a new transport task. This interface mode could be useful when one task has insufficient robots, for instance, because the object to be transported requires extra effort. Fig. 3.5 shows two team of robots performing collective transport while the operator rearranges the robots and assigns them to an incomplete task.

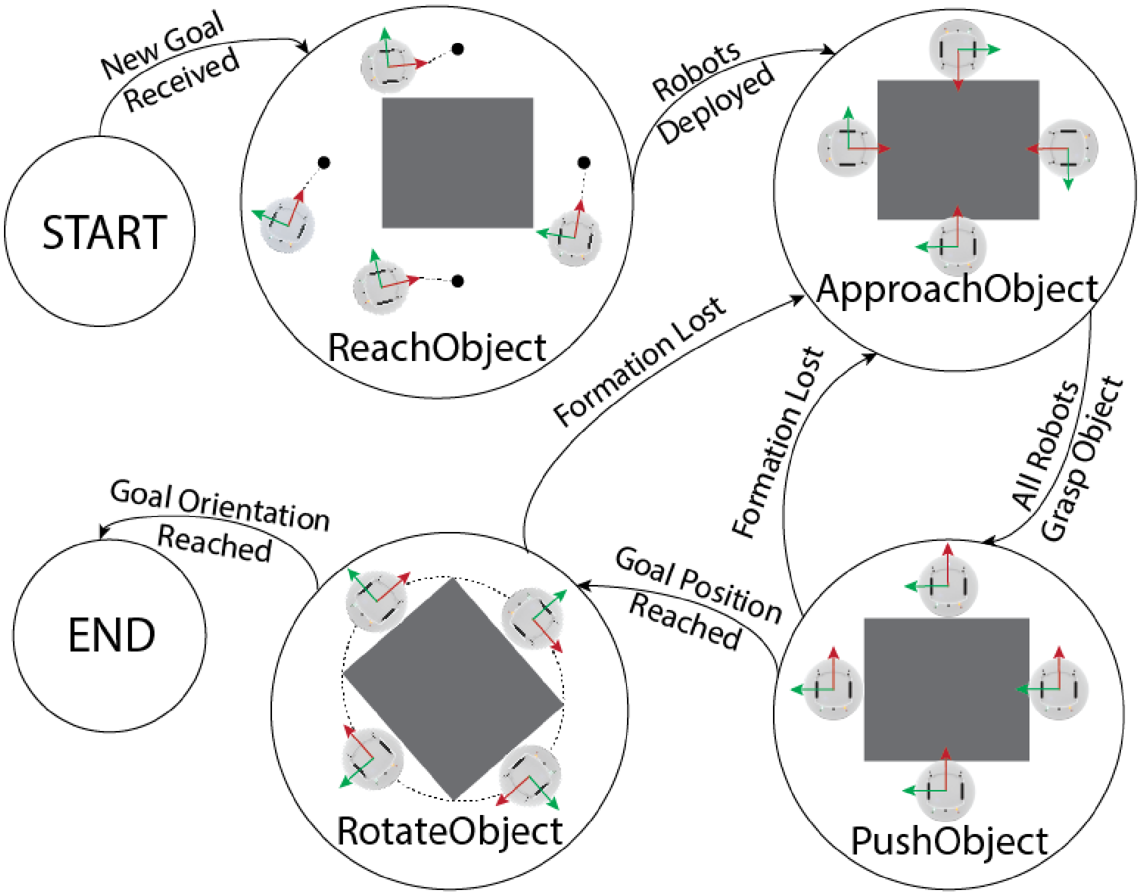


Figure 3.6: Collective transport state machine.

3.2.4 Collective Transport

The collective transport behavior is structured into a state machine, as shown in Fig. 3.6. Since the focus of the chapter is on the operator interface, I kept the transport behavior as simple as possible, but sufficiently effective to act as a meaningful use case for the interface. Designing a more complex, or more decentralized transport behavior is beyond the scope of this work. The states in the Finite State Machine (FSM) are described next.

ReachObject. The robots calculate the direction vector to the assigned object, and then navigate while avoiding obstacles. Depending on the number of robots assigned to an object, the deployment positions are generated in a circular fashion around the object, resulting in a team of robots caging their assigned object. New deployment positions are generated every time a robot is removed from or added to a team. The state comes to an end once all the robots reach their deployment positions.

ApproachObject. From the deployment positions, the robots move towards the centroid of the object. The state ends when all the robots are in contact with the object.

PushObject. The robots rotate in place facing the direction of the goal and start moving at the same speed towards the goal. In particular, the front robot adjusts its speed while maintaining a specific distance from the object. This feature prevents the robots from breaking formation while pushing the object. In case a robot loses the formation, the robots re-deploys and re-approaches the object. The state ends successfully when the object reaches the goal position.

RotateObject. All robots rotate in place facing outwards in a circular manner, and move along a circle to rotate the object. In case a robot breaks the formation, the robots re-deploys and re-approaches the object. The state ends successfully when the object's orientation is within an acceptable value with the respect to the goal orientation.

3.3 Experimental Analysis

In this section, I analyze the performance of the collective transport behavior and the usability of the app interface assessed through an operator study.

3.3.1 Transport Behavior Analysis

As a preparatory step towards the operator study, I characterized the performance of the transport behavior to ensure that the task completion rate was within acceptable bounds. I also evaluated the need for human intervention in completing the task when there are insufficient robots in a team.

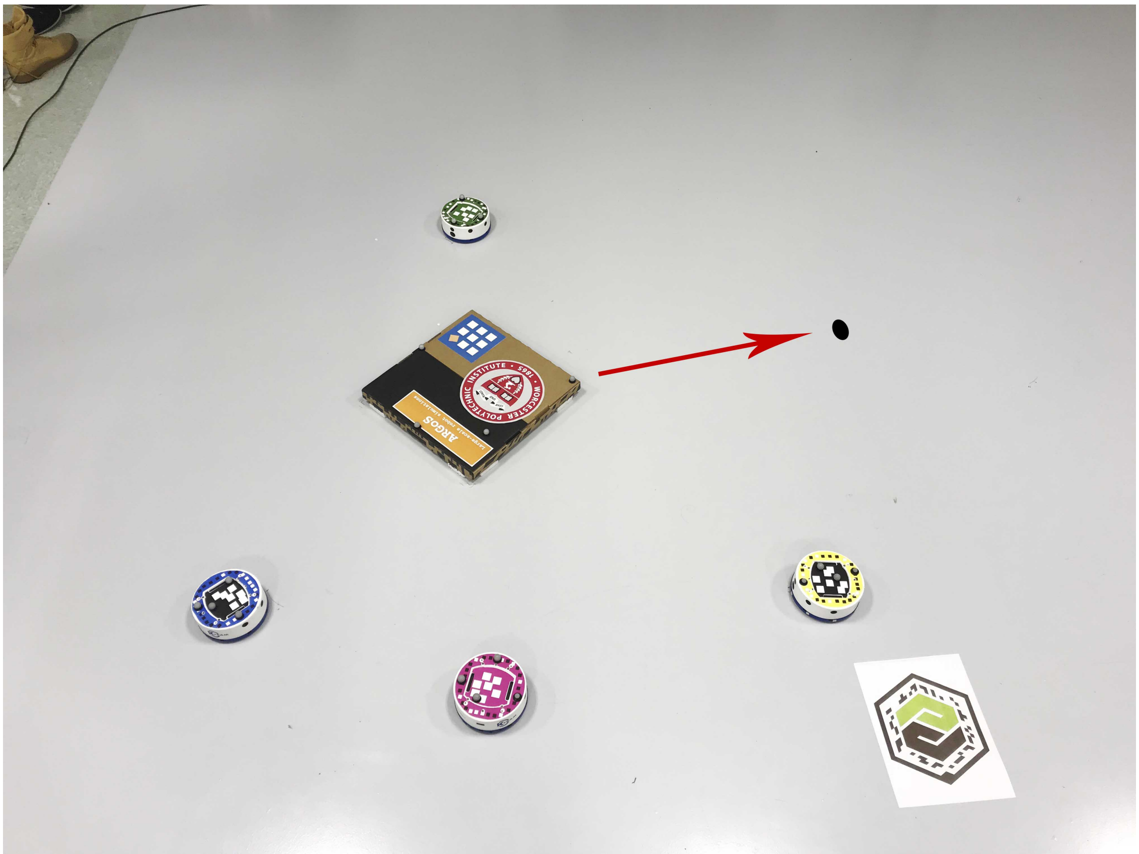


Figure 3.7: The setup of Experiment 1. The overlaid red arrow and black point indicate the direction and position of the object to be transported by the robots.

The aim of Experiment 1 was to transport one object to a predefined target pose using a team of four robots. In Experiment 2, the robot team had to transport two objects to a predefined goal pose using five robots. In Experiment 2 a human was present in case robots had to be reassigned from a task to another.

Experiment 1: Setup. I performed 10 consecutive trials of collective transport of an object with four robots (Fig. 3.7) to achieve a predefined pose ($x = 0\,\mathrm{m}$, $y = -1\,\mathrm{m}$, $\theta = 152°$). The starting positions of the object and the robots remained the same for all trials. To minimize the effect of spurious failures not related to my algorithm, I selected the target pose according to (i) the coverage of the motion capture system across the arena and (ii) the presence of floor irregularities.

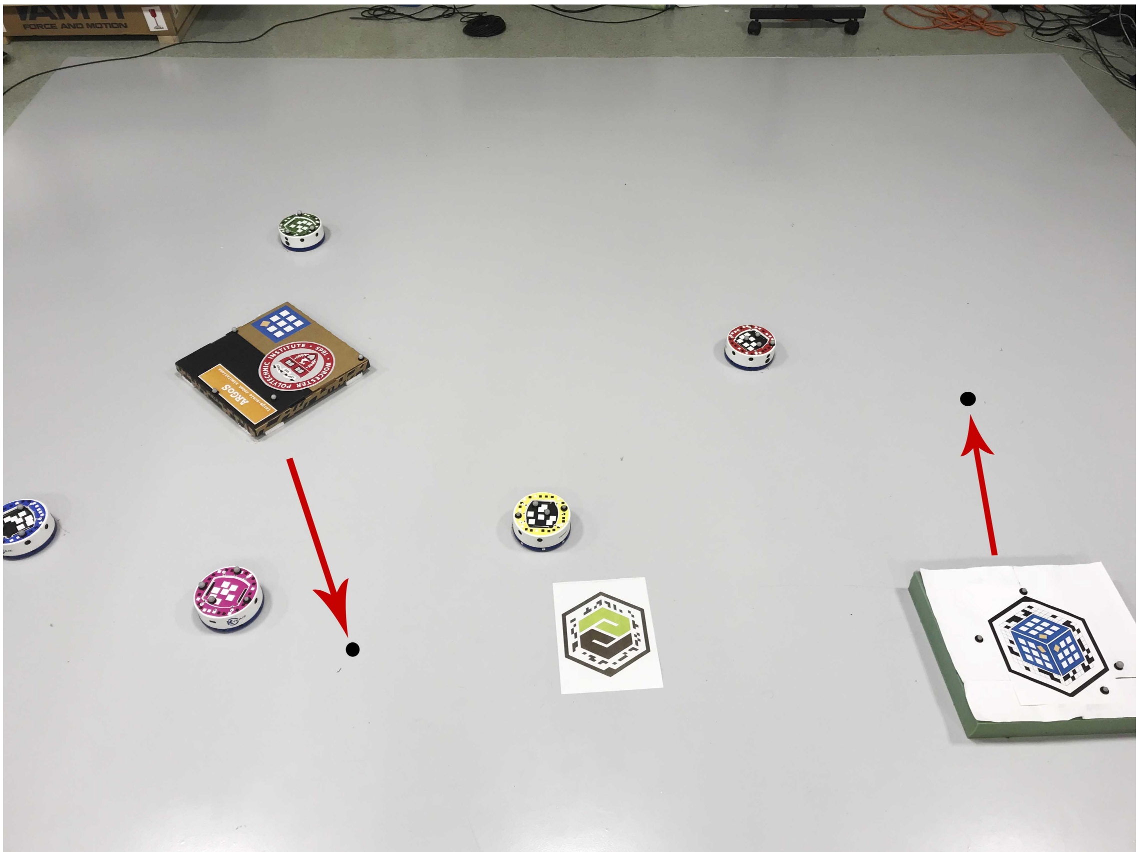


Figure 3.8: The setup of Experiment 2. The overlaid red arrows and black points indicate the directions and positions of the objects to be transported by the robots.

Table 3.1: Statistics on data collected from Experiment 1

Data type (unit)	Min	Max	Median	Mean
Error on x (m)	0.0443	0.0635	0.0571	0.0563
Error on y (m)	0.0325	0.0538	0.0461	0.0450
Error on θ (°)	0.0290	1.3250	1.1085	1.0098
Completion Time (s)	121.2	148.9	123.1	128.5

Experiment 1: Results. Statistics about the recorded final positions and orientations across the 10 trials are reported in Table 3.1. The absolute position errors are in meters and the absolute orientation error is in degrees. The data shows that the collective transport behavior is very efficient in moving the object, as errors are on average in the order of cm and faction of a degree. The average completion time, about 2 minutes, is also adequate for tests involving untrained operators.

Table 3.2: Statistics on data collected from Experiment 2, two object transport with human operator's presence.

Object ID	Data type (unit)	Min	Max	Median
Obj1	Error on x_1 (m)	0.0193	0.0709	0.0477
	Error on y_1 (m)	0.0130	0.1022	0.0493
	Error on θ_1 (°)	0.5170	1.2540	0.8905
	Completion Time (s)	134.20	232.10	159.35
Obj2	Error on x_2 (m)	0.0004	0.0507	0.0060
	Error on y_2 (m)	0.0435	0.1171	0.0862
	Error on θ (°)	0.3799	1.1758	0.8422
	Completion Time (s)	295.9	402.1	363.3

Experiment 2: Setup. I performed 10 consecutive trials of collective transport of two objects, Obj1 and Obj2, with five robots (Fig. 3.7) beginning from the same position for all trials. Each object had to reach a predefined pose ($x_1 = 0.8\,\mathrm{m}$, $y_1 = 0\,\mathrm{m}$, $\theta_1 = 128\,°$) and ($x_2 = -1\,\mathrm{m}$, $y_2 = 0.5\,\mathrm{m}$, $\theta_2 = 46°$) respectively. I performed all the trials with a human-in-the-loop to reassign the robots to Obj2 upon completion of Obj1's transport.

Experiment 2: Results. Table 3.2 shows the statistics of absolute position and orientation errors collected at the end of 10 trials. As Obj2 had only one assigned robot, the task stayed idle until Obj1 reached its goal pose and sufficient robots were reassigned by the operator to Obj2. I kept track of the time at which the human interacts through the interface. The median time I observed was 171.65 s, with a minimum of 143.9 s and a maximum of 244.5 s. These values are greater than the completion time of Obj1. This indicates that Obj2 was usually transported after the human interacted with the system. Hence, Obj2 would not have been transported to the destination without human intervention.

3.3.2 Usability Analysis

Experimental Setup. I conducted an operator study of 10 participants from multiple disciplines. The operators' ages ranged between 20 and 29. The experiment in which every operator was involved was divided into two halves, with one task to complete for

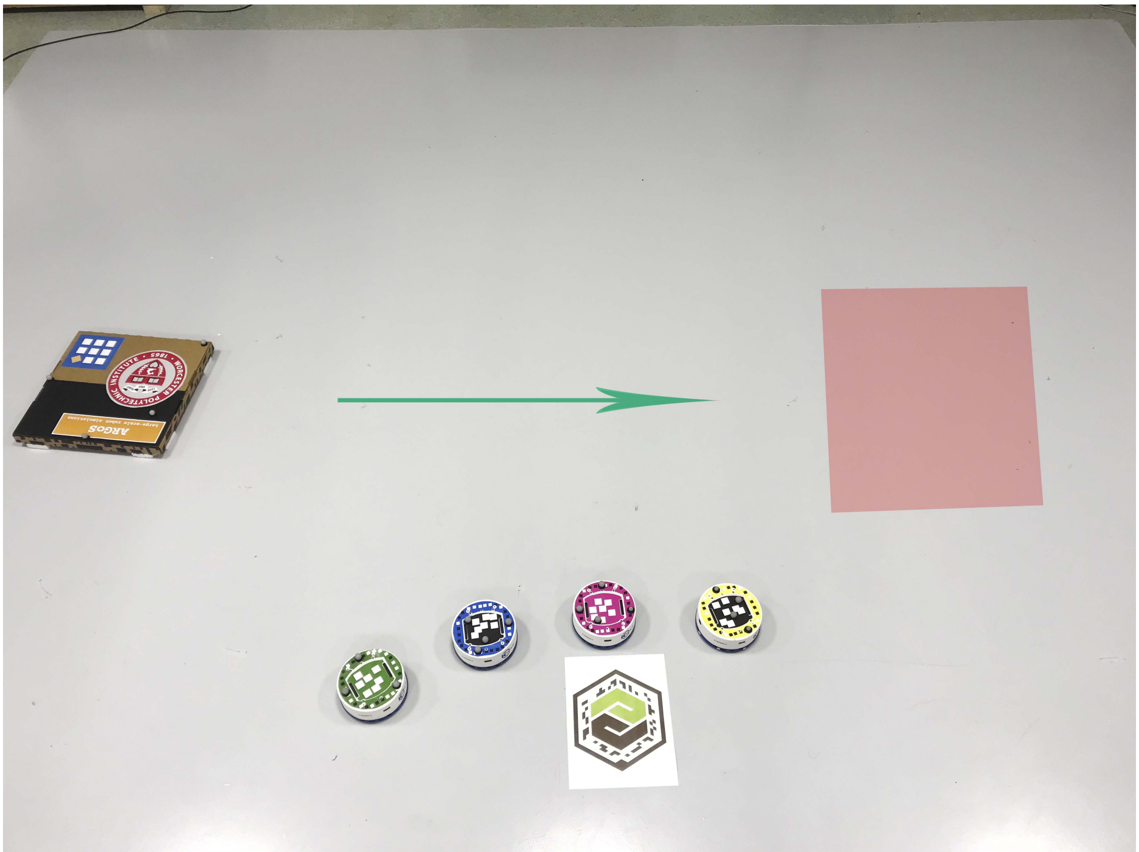


Figure 3.9: User study experimental setup. The overlaid green arrow indicates the direction of the object to be transported by the robots. The overlaid red region indicates the goal region in which the object needs to be translated.

each half. After each half, the participants were asked to fill out a questionnaire based on NASA TLX [89] subscales using a Likert Scale [143] for quantifying their response. All the participants had no prior experience of interacting with the system.

Task Information. Both tasks involved transporting an object to the goal region (Fig. 3.9) using the interface. The participants had to focus on only translation of the object and not the orientation. The task ended when the object completely entered the goal region. In Task1, the participants could only control up to four robots manually (a purely robot-oriented interaction). In Task2, the participants could interact with the object (environment-oriented) and with the robots (robot-oriented).

Results. To quantify the reactions of the participants during the experiments, I em-

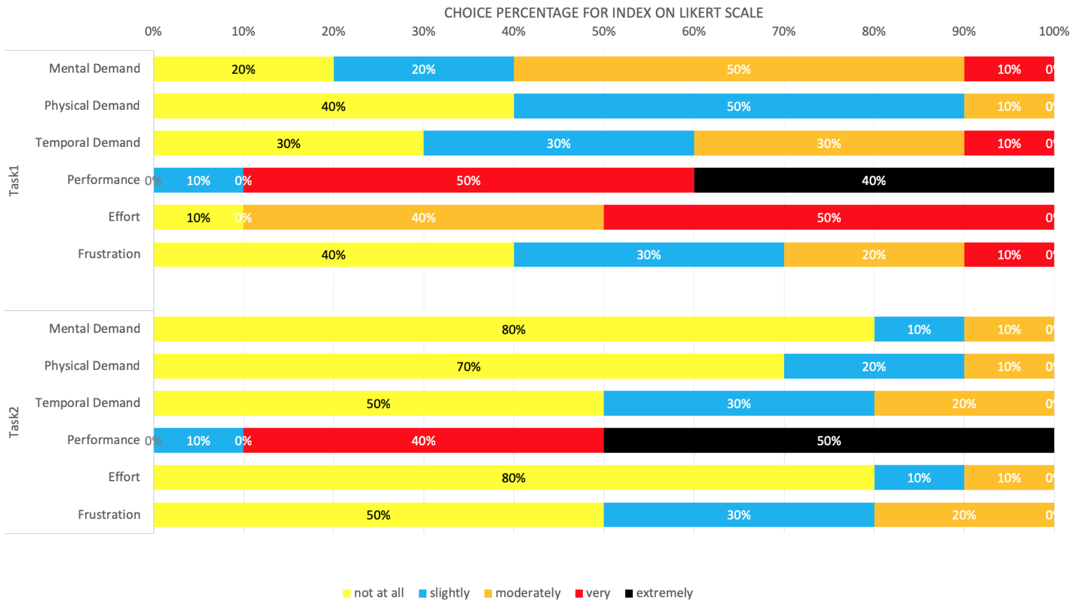


Figure 3.10: Percentage of raw scores using NASA TLX subscales on the Likert scale from the questionnaire submitted by operators after the study.

ployed the NASA TLX scales on a Likert Scale and the results are shown in Fig. 3.10. The percentage in the plot depicts the number of responses made for a particular scale index. Fig. 3.11 reports the results of the comparative study, where the participants were asked to indicate which task caused a more significant cognitive load. The comparative study shows that Task2, in which both environment- and robot-oriented interactions were allowed, has a lower cognitive load with respect to Task1, which only allowed robot-oriented interactions. The results of Fig. 3.11 confirm the raw scores displayed in Fig. 3.10. Further evidence supporting my claim that combining environment- and robot-oriented interactions is beneficial is provided by the number of interactions recorded during the experiments. The data is reported in Table 3.3, and it clearly shows that combining the two modalities entails a lower number of operations than purely robot-oriented approaches.

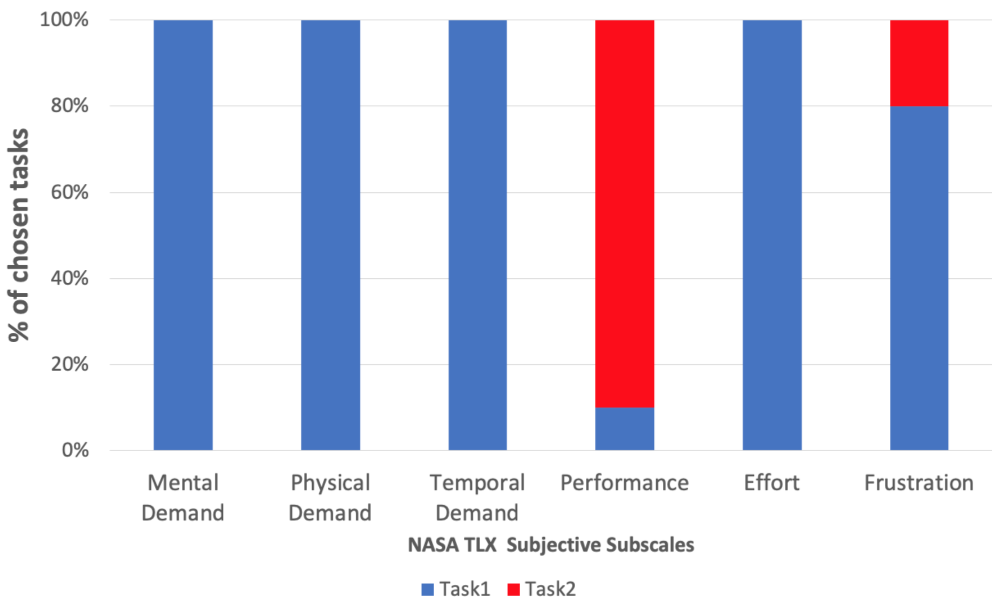


Figure 3.11: Comparative cognitive load.

Table 3.3: Statistics on number of interactions made with the interface by the operator in both the task during the user study.

	No. of Interactions		
Task ID	Min	Max	Median
Task 1	8	118	52
Task 2	1	8	1

3.4 Chapter Summary

In this chapter, I proposed a human multi-robot interface that combines environment-oriented and robot-oriented modalities of interaction. I based the interface on an app for a hand-held device, because of both the low cost of this solution and the intuitiveness of touch-based graphical interfaces. The interface and the associated infrastructure are designed to work with simulated as well as real robots, although in this chapter I focused the analysis on real-robot experiments. I performed a user study to validate the effectiveness of my interface. Results confirmed that, for a task such as collective transport, the ability to mix environment-oriented commands and robot-oriented ones is beneficial, because it results in a lower number of required commands to achieve the goal.

In a broader perspective, this chapter suggests that the specifics of the task a robot must complete plays an important role in the definition of human multi-robot interfaces. As discussed in [122], environment-oriented interactions might not scale well for tasks that involve diffusion of many robots in cluttered environments. However, for tasks such as collective transport, in which the robots are tightly connected to the object to carry, the ability to focus on the object makes the interaction more effective.

Chapter 4

Operator Engagement

Due to the potentially large number of units involved, the interaction with a multi-robot system is likely to exceed the limits of the span of apprehension of any individual human operator. In chapter 3, I studied how this issue can be tackled by interacting with the robots in two modalities — environment-oriented and robot-oriented. In this chapter, I explore how this modality of interaction affects the performance of multiple cooperating operators.

However, with multiple humans in the system, additional challenges arise, such as coping with ineffective group dynamics [4], unbalanced workload [35, 158], and inhomogeneous awareness [130, 180, 193]. These challenges coalesce in a common, undesirable phenomenon: the *out-of-the-loop (OOTL) performance problem*, caused by a lack of engagement in the task, awareness of its state, and trust in the system and other operators [66, 84].

Little research exists on these topics in the context of multi-robot systems. Hence, through a user study involving 28 human operators and 8 real robots, I study how the concept of mixed granularity in multi-human multi-robot interaction affects operator engagement, awareness, and trust while balancing the workload between multiple operators.

This chapter offers two main contributions:

- From the technological point of view, I created the first mixed granularity interface for multi-human-multi-robot interaction. Our interface is based on a networked mixed reality application that allows the operators to visualize and modify the global state of the system collaboratively on common tablets and smartphones.

- From the scientific point of view, I assessed the validity of my approach through a user study of the interface in terms of workload, trust, and task performance. The user study involved 14 teams of 2 operators each, controlling a team of 8 robots in a collective construction scenario.

The chapter is organized as follows. In Sec. 4.1 I discuss related work on human-robot interfaces. In Sec. 4.2 I present my system and its design. In Sec. 4.3 I detail the user study, followed by a discussion of the results in Sec. 4.4. I summarize the chapter in Sec. 4.5.

4.1 Related Work on Operator Engagement

According to Endsley [65], granularity of control is a key aspect affecting the OOTL performance problem. Low-level control includes robot selection and manipulation [5, 85, 113, 137, 139, 167, 169, 187, 244], while high-level control comprises of global goal manipulation by defining navigation goals [9, 14, 57, 122], team organization [56, 107], or allocating tasks [153]. Limiting control to one type of granularity creates a fundamental tradeoff [65]. Low-level control offers more opportunity for interaction and sense of trust in the system, but it causes higher workload and stress. Conversely, high-level control limits the amount of workload, often leading to boredom and lower situational awareness, which in turn results in the OOTL performance problem.

There exists little research on supervisory control in multi-human-multi-robot systems. Several papers study the case in which humans play the role of a bystanders in, e.g., navigation of robots in a shared environment [10, 47, 92, 99, 222, 229] and human

Figure 4.1: System overview with multiple human operators.

tracking [43, 101, 176, 176, 232, 248]. Other works focus on how to coordinate teams of humans and robots [15, 74, 107, 108, 152, 221, 243]. In supervisory control, past work focused on investigating the influence of autonomy and resource sharing on the task performance [137, 139]. Researchers also investigated the effects of curiosity and training on increasing task performance [244]. However, to the best of my knowledge, there has not been any study on the out-of-the-loop performance problem in the context of multi-robot systems.

4.2 Multi-Human Multi-Robot Interaction Interface

4.2.1 System Overview

The system is an extension of the design discussed in Section 3.2.1 with a capability to handle multiple human operators in the system. The extended system is comprised of four components (see Fig. 4.1):

1. A distributed mixed reality interface implemented as an app for a hand-held device;
2. A team of robots pre-programmed with several autonomous behaviors, including a basic “go-to-location” and a more advanced “collective transport”.
3. A Vicon motion tracking system for localizing the robots and dynamic objects in the environment;
4. ARGoS [186], a multi-robot simulator acting as a middleware responsible for channeling data to the robots.

The process starts when an operator specifies a new position for an object, the selected team of robots, or an individual robot on a hand-held device. The hand-held device then broadcasts this information over the Wi-Fi network for other active MR app operators and ARGoS. The other MR apps process and display the broadcasted change in the local augmented view. ARGoS generates and broadcasts the goals for the robots, which execute the requested operations.[1]

4.2.2 Mixed Reality Interface

The interaction between operators and robots occurs through an mixed reality (MR) application installed on handheld devices, such as smartphones or tablets. The app

[1] A video demonstration of the system is available at https://youtu.be/QGUYfBB9Ves.

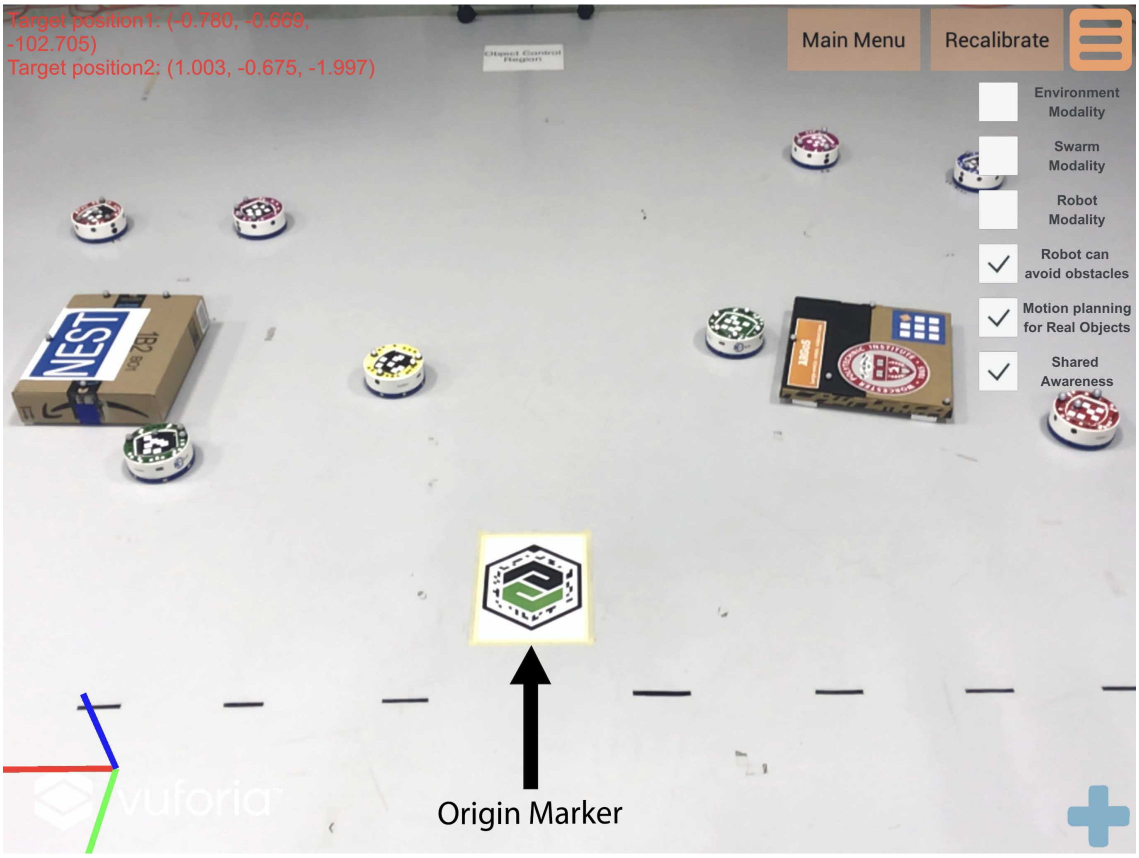
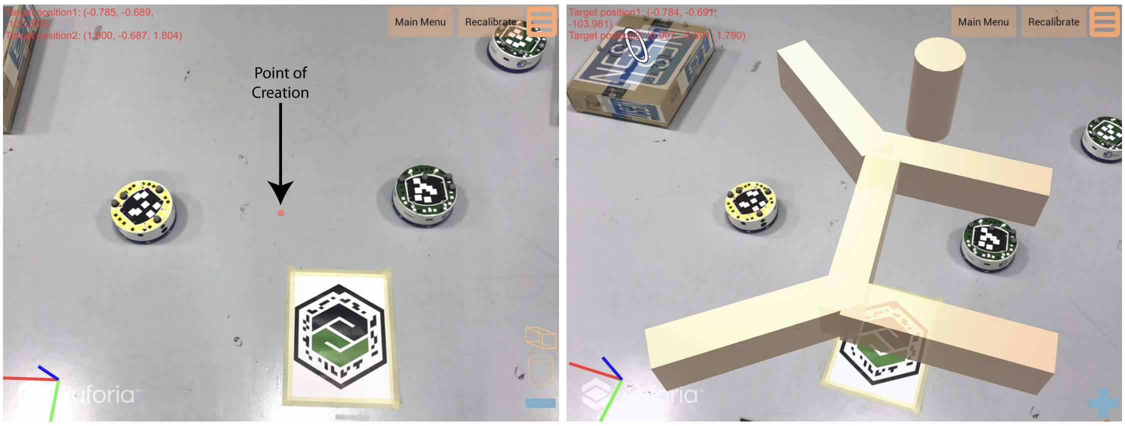


Figure 4.2: Screenshot of the MR Interface running on an iPad. The overlaid black arrow indicates the origin marker for initializing the coordinate frame of the interface.

integrates Vuforia [2], a software development kit for MR applications, and the Unity Game Engine [67]. The application can recognize the objects and the robots in real time using fiducial markers. The operator can visualize and manipulate the identified objects and robots by means of a virtual object overlayed on the real robot in the device screen. The virtual object can be translated using a one-finger swipe and rotated using a two-finger twist. The application also lets the operator select some or all of the robots with a one-finger swipe. Fig. 4.2 shows the screenshot of the MR application. The top-left corner displays the desired object position. The bottom-left corner depicts the current reference frame based on the location of the operator and the unique origin marker. The top-right corner offers the menu buttons for controlling additional functionality such as re-calibration,



(a) Virtual object creation mode (b) New virtual objects created and moved

Figure 4.3: Virtual object creation and manipulation. The overlaid black arrow indicates the point of virtual object creation.

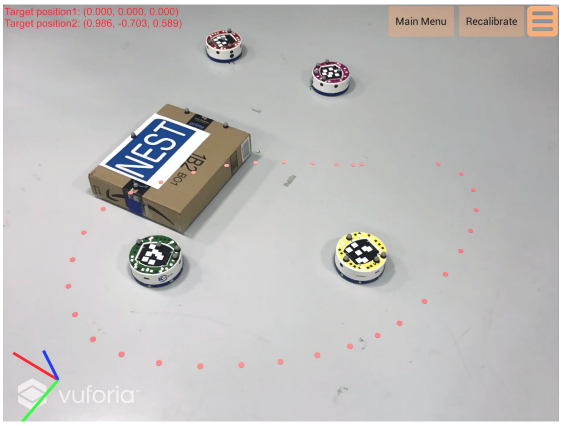
toggling obstacle avoidance and toggling visibility and detection of objects and robots. The bottom-right corner houses the button for creating virtual objects dynamically.

4.2.3 Control Granularity

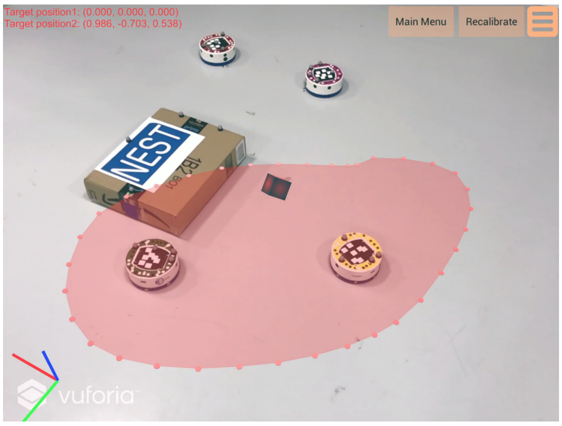
This interface includes the interaction modes discussed in Section 3.2.3 and extends the system by adding the following modes of interaction.

Virtual Object Creation, Manipulation and Deletion. The app allows an operator to create virtual cuboids and virtual cylinders dynamically. The operator can reposition and reorient these objects. During virtual object creation, the app shows a point on the ground to signify the creation of virtual objects on that point (see Fig. 4.3a). The operator can delete the created virtual object with a two-finger long-press gesture. This modality is useful for creating virtual obstacles/walls and for defining a separate operating region for multiple operator scenario. Fig. 4.3 shows the virtual objects arranged in the environment.

Robot Team Selection and Manipulation. With a one-finger swipe, the operator can define an enclosed space for selecting all the robots physically present in that region. A virtual layer overlays on the selected region and a virtual cube appears at the centroid of

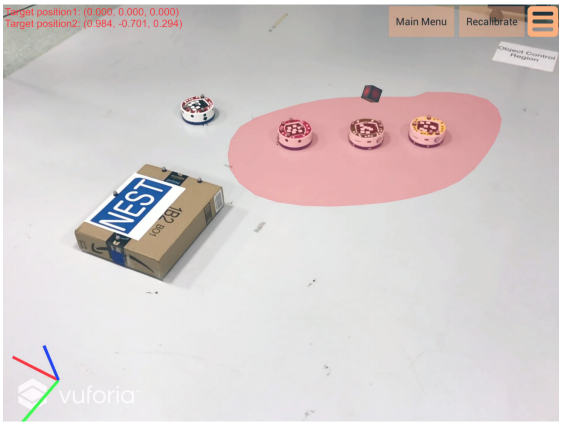


(a) Robot team selection



(b) Robot team creation

(c) Robot team manipulation



(d) Robot team re-positioned

Figure 4.4: Robot team creation and manipulation by interacting with the interface. The overlaid dotted black arrow indicates the one-finger swipe gesture to move the virtual cube for re-positioning the the team of robots.

this virtual layer. The operator can manipulate this cube to define a goal position for all the robots in the region. The robots then reposition themselves similarly to the Robot Manipulation modality. An operator can select only one team of robots at a time, and every time a new team of robots is selected, the app clears the last selection. If two or more operators have the same robot in their selected team, then the robot receives the most recent goal position. Fig. 4.4a and Fig. 4.4b shows the selection of a group of robots. Fig. 4.4c shows the manipulation of the virtual cube to define a new goal position for the team of robots. Fig. 4.4d shows the robots navigating to the desired position.

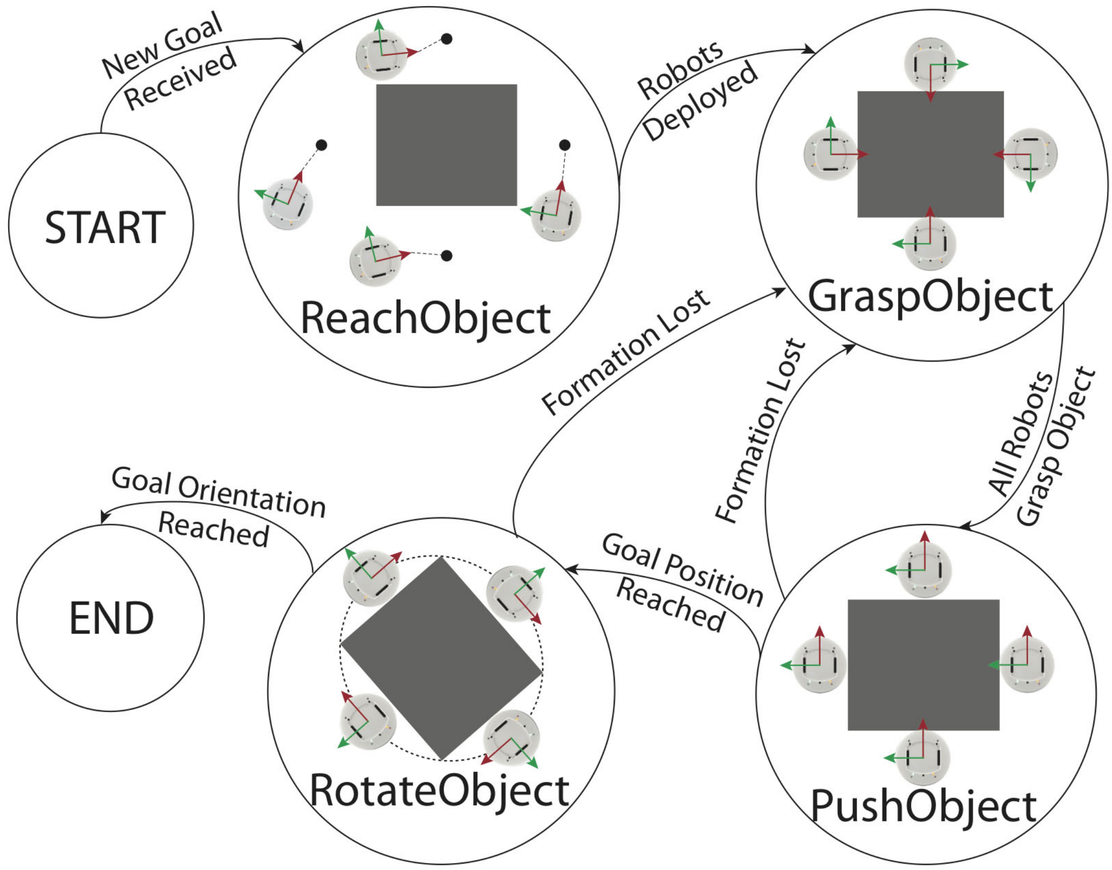
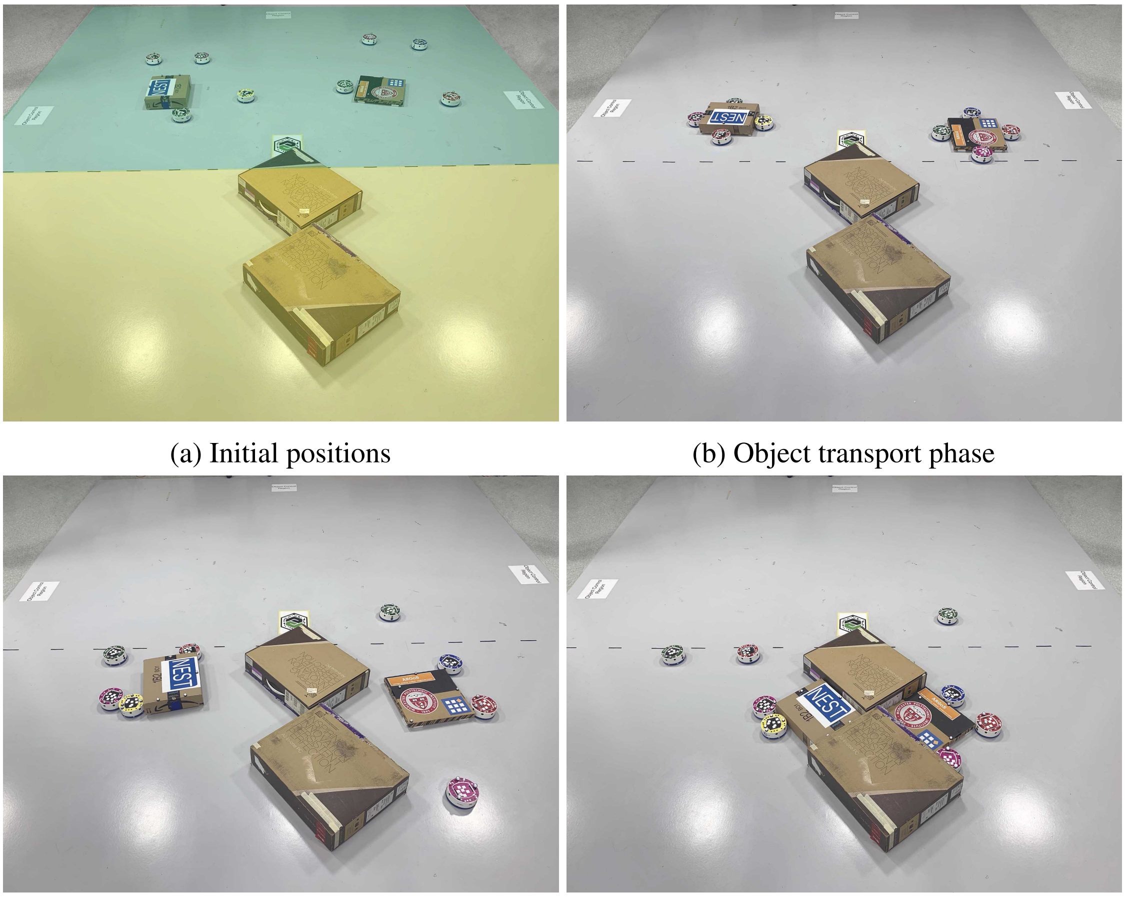


Figure 4.5: Collective transport state machine

4.2.4 Shared Awareness

The app broadcasts the modality changes performed by an operator. Other hand-held devices receive these changes and reflect them in the augmented view, thus making all the operators aware of the changes. The app shares this information in real time, showing the virtual objects as they are manipulated by other operators. This feature is useful to facilitate teamwork, to share information on what an operator is currently controlling, and to avoid conflicting control of a specific virtual object.



(a) Initial positions (b) Object transport phase

(c) Robot control phase (d) Desired structure

Figure 4.6: Experimental setup of the user study. The overlaid green region indicates the transport region. The overlaid yellow region indicates the placement region.

4.2.5 Collective Transport

I employ the simple collective transport behavior based on the finite state machine (FSM) shown in Fig. 4.5. This behavior is identical to the one presented in Section 3.2.4.

4.3 User Study

4.3.1 Experimental Setup

I designed a user study scenario in which two operators (O1 and O2) had to supervise 8 robots in the construction of a simple structure. Because I focus on the potential benefits of mixed granularity of control (MGOC), in our experiments I considered two scenarios: one in which both operators used MGOC, and one in which the operators were forced to use a single granularity of control (SGOC).

Phases. The construction scenario is composed of two phases. In Phase 1, the robots must transport an object in the general vicinity of its target position. In Phase 2, the object must be pushed into its target position as precisely as possible. For the task to be completed, the robots must place two such objects. Fig. 4.6a shows the initial positions of the robots and the objects in the field.

Scenarios. I considered two scenarios. In the *MGOC scenario*, the operators are given the possibility to control the robots with the full capabilities of the app. In addition, the operators are free to work in any way they desire: they can work sequentially, collaborating on the first object and then on the second; or they can work in parallel, focusing on different objects. In contrast, in the *SGOC scenario*, I established specific roles and modalities of interaction for the operators. I divided the field into two regions: the *transport region* (corresponding to Phase 1) and the *placement region* (corresponding to Phase 2). I assigned a specific operator to each region, and prevented operators from working outside of their region: operator O1 was assigned to Phase 1 (transport), and operator O2 was assigned to Phase 2 (placement). Motivated by the results of Chapter 3, in the *transport region* I allowed the operator to only use object manipulation. On the other hand, in the *placement region*, I allowed the operator to only use robot control. Fig. 4.6b shows the collective transport behavior in the *transport region* and Fig. 4.6c shows the robots controlled in the *placement region*. Fig. 4.6d shows the desired structure that the participants had to achieve for completing the task. The dashed black line divides the field into the two regions.

4.3.2 Participant Sample

I recruited a total of 28 students with ages ranging from 21 to 30 years old (average $=$ 24.04 ± 2.74). None of them had prior experience with the system.

4.3.3 Procedures

Each session of the study approximately took 75 minutes and involved two participants. The participants first engaged in the two scenarios sequentially, and the order of the scenarios was randomized to avoid any learning effects. At the beginning of each scenario, we briefly explained to the participants the task they had to perform and gave them 5 minutes to explore the app. The participants answered a questionnaire after completing each scenario.

4.3.4 Metrics

I recorded each participant's task activity metrics. In addition, I collected the responses to the post-scenario questionnaire. I evaluated the following metrics:

Workload. I employed the NASA TLX scale [89] for the participants to compare the workload during each scenarios. The participants had to rank scenarios for each attribute of the scale. I used a Borda count [20] to find a winner based on the ranks assigned by the participants. I also recorded the number of operator interactions (e.g., number of touches and gestures on the app).

OOTL phenomenon. I evaluated the OOTL performance problem by quantifying situational awareness, which is the main factor for its occurrence [65]. To quantify situational

Table 4.1: Borda count results of comparison study for workload based on NASA TLX scale attributes. The gray cell indicate the leading scenario for each attribute. The mark $^-$ denotes negative scales. Lower ranking is better.

	O1		O2	
NASA TLX Attributes	SGOC	MGOC	SGOC	MGOC
Mental Load$^-$	15	27	23	19
Physical Load$^-$	18	24	21	21
Temporal Load$^-$	17	25	19	23
Performance	21	21	19	23
Effort$^-$	15	27	21	21
Stress$^-$	20	22	21	21

awareness, we employed the Situational Awareness Rating Technique (SART) [205]. The participants had to rank the scenarios for each attribute. I used a Borda count to determine the leading scenario based on the ranks assigned. Additionally, I recorded the activity period (AP) of the participants during the scenario to analyze the total duration of time they were active. I measured AP as the percentage of time a participant was interacting with the system.

Trust. I employed the group trust scale [4] to analyze the trust between human teammates during a scenario, and the human-robot trust sub-scale [201] to analyze the trust in the robots' behavior. The participants had to rank the scenarios based on these scales. I used a Borda count to determine the leading scenario.

Task Performance. To assess the overall performance of the system in completing construction, I considered the time elapsed between the start of a scenario and the moment in which the second object was placed in its final destination.

4.3.5 Results

Workload. Table 4.1 reports the results of the workload comparison study for operators O1 and O2. In the MGOC scenario, both O1 and O2 could choose how to interact with the system and what to work on. In the SGOC scenario, O1 had to perform transport with

Table 4.2: Borda count results of comparison study for situational awareness based on SART scale attributes. The gray cells indicate the leading scenario for each attribute.

	O1		O2	
SART Attributes	SGOC	MGOC	SGOC	MGOC
Complexity	16	26	20	22
Changeability	18	24	20	22
Variable	16	26	20	22
Arousal	18	24	21	21
Concentration	16	26	24	18
Mental Capacity	15	27	23	19
Information Gain	19	23	22	20
Familiarity	23	19	19	23

the object modality, while O2 was forced to perform placement with the robot modality. The results show that, for O1, MGOC is much more demanding than SGOC, while for O2 the workload in both scenarios is approximately equal. These results are also confirmed in Fig. 4.7, which reports the box plot for interactions made with the hand-held device. Because the samples of the number of interactions in MGOC and SGOC are paired and non-parametric in nature, I use a Friedman test [75] for statistical analysis. Setting a p-value of 0.01 to establish statistical significance, I concluded that the difference in number of interactions is significant (Friedman test: $p = 0.0001$, $\chi^2 = 14.000$) between operators in SGOC, while the difference in number of interactions is not significant (Friedman test: $p = 0.109$, $\chi^2 = 2.571$) in MGOC. These results indicate an imbalance in workload between operators in SGOC, leaving O1 out of the loop.

OOTL performance problem. Table 4.2 reports the results of the situational awareness comparison study for O1 and O2. For O1, the SGOC scenario demands little attention; when compared with MGOC, the data indicates that the latter results in a much higher engagement of the operator in the task, while with SGOC the operators feel more out of the loop. In contrast, O2's levels of engagement and awareness are comparable across the two scenarios. This interpretation is compatible with the data shown in Fig. 4.2, which

Table 4.3: Borda count results of comparison study for trust based [4] and [201]. The gray cells indicate the leading scenario for each attribute. The mark $^-$ denotes negative scales. Lower ranking is better.

	O1		O2	
H-H Trust Attributes	SGOC	MGOC	SGOC	MGOC
Honest	17	25	19	23
Trustworthy	18	24	20	22
Alert	18	24	20	22
Help	20	22	16	26
Will to Help	17	25	16	26
Acceptance	19	23	17	25
H-R Trust Attributes	SGOC	MGOC	SGOC	MGOC
Function Success	21	21	21	21
Dependable	18	24	20	22
Reliable	19	23	20	22
Predictable	21	21	20	22
Consistence	20	22	18	24
Feedback	19	23	20	22
Meet the Needs	19	23	20	22
Provide Information	22	20	19	23
Communication	19	23	20	22
Performance	19	23	20	22
Follow Directions	20	22	19	23
Unresponsive$^-$	20	22	22	20
Errors$^-$	21	21	23	19
Malfunction$^-$	21	21	23	19

reports the percentage of the active period of both operators in each scenario. Because the samples of the activity period data are paired and non-parametric in nature, I again used a Friedman test for statistical analysis. Setting a p-value of 0.01 to establish statistical significance, I concluded that the difference in activity period is statistically significant between operators in SGOC (Friedman test: $p = 0.0001$, $\chi^2 = 14.000$), while in MGOC the difference in activity period is not (Friedman test: $p = 0.248$, $\chi^2 = 1.333$).

Trust. Table 4.3 reports the results of the trust comparison study for O1 and O2. Both O1 and O2 reported higher trust in MGOC than in SGOC.

Task Performance. Fig. 4.9 shows a box plot of task performance for SGOC and

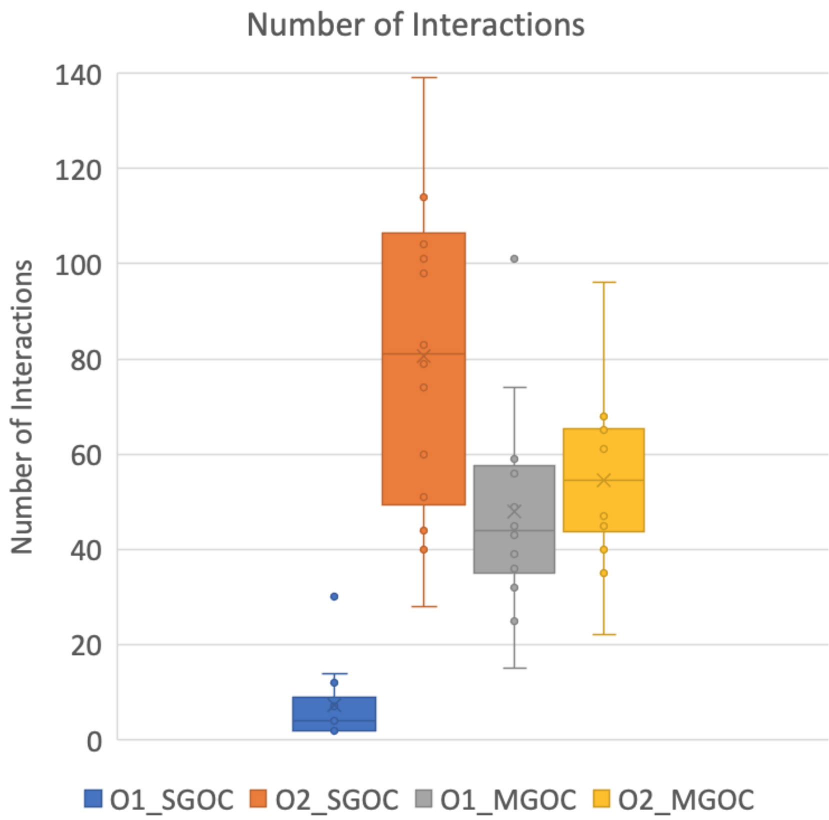


Figure 4.7: Number of interactions made with the hand-held device for both tasks by operators O1 and O2

MGOC. Because the samples of the performance data are paired and non-parametric in nature, I again used a Friedman test for statistical analysis. Setting a p-value of 0.05 to establish statistical significance, I concluded that the difference in activity period is not statistically significant between SGOC and MGOC (Friedman test: $p = 0.109$, $\chi^2 = 2.571$). The median completion times I observed were 10.63 min and 7.93 min for SGOC and MGOC, respectively. The median suggests that MGOC outperforms SGOC in terms of completion time.

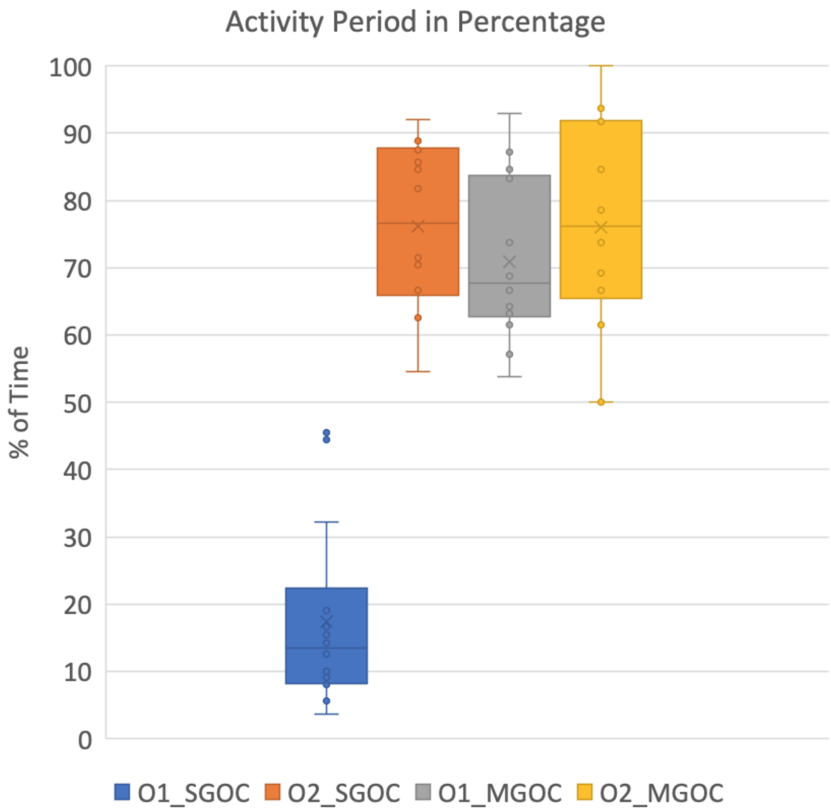


Figure 4.8: Activity Period in percentage of time for O1 and O2 during each scenario.

4.4 Analysis and Discussion

The results of the user study allow us to draw a number of interesting conclusions about the nature of multi-human multi-robot interaction.

First, the case in which the operators are given an equal role (MGOC scenario) corresponded with the best system performance. While I never suggested to the operators how to structure their work, all the operators pairs quickly settled on working in parallel on both phases. Often, one operator completed her task faster than the other—in this case, the faster operator switched to help the slower one. This resulted in both operators being constantly engaged in the task and also in a better sense of mutual trust and teamwork.

In contrast, when I forcefully assigned specific roles and modalities of interaction, I

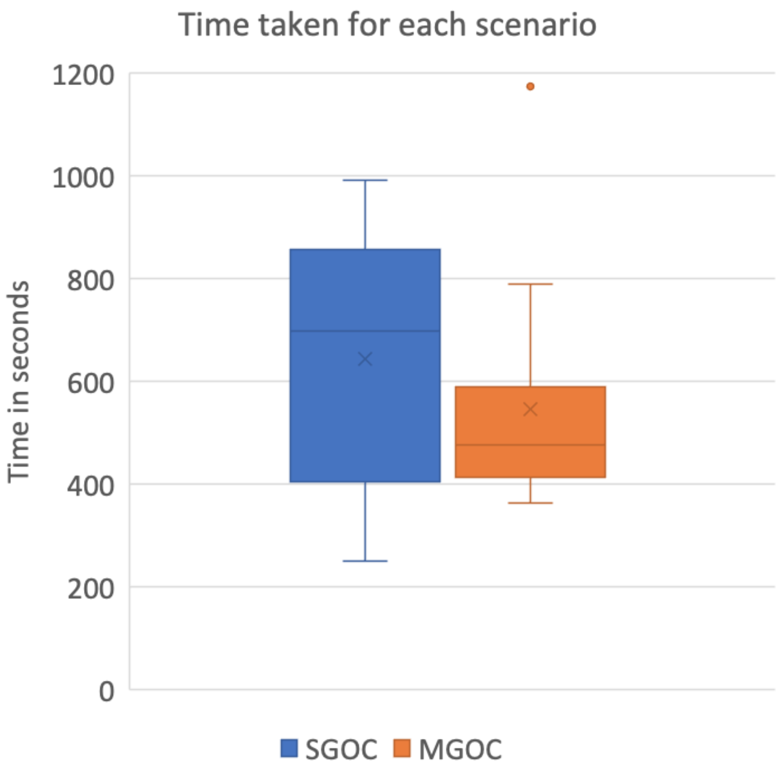


Figure 4.9: Performance recorded in terms of time taken to complete each task.

found that the operator with a lower workload became easily distracted from the task. It is important to notice that, in Phase 1, the most efficient option to complete the task is object manipulation, while in Phase 2 it is robot manipulation. These modalities were also preferred in the MGOC scenarios when the operators acted in parallel. Therefore the only significant difference between SGOC and MGOC was in the forced role assignment.

Our results are consistent with [65] and suggest that, when distributing control responsibility across operators, the OOTL problem affects the system performance. The operators prefer to reach their limit of apprehension and remain engaged in the system, rather than having long periods of inactivity followed by sudden moment of high load. In addition, the latter scenario might prove stressful because of the difficulty of catching up quickly when a system composed of many parts presents itself in an unknown state that demands attention.

As a consequence, specialization across operators (the SGOC scenario) is not necessarily the best option. In designing the roles of the operators of a multi-robot system, special attention must be paid to balancing the workload, keeping engagement high, and allowing for a healthy level of overlap across operators, to foster the kind of teamwork I observed in the MGOC case. In our user study, 25 out of 28 participants reported that they prefer the MGOC scenario over the SGOC one. Different tasks, robot behaviors, and applications might reveal more complex phenomena. More research is required to understand the connection between these issues and the challenge of increasing human performance in an automated system.

4.5 Chapter Summary

In this chapter, I study the role of the out-of-the-loop (OOTL) phenomenon in the context of multi-human multi-robot interaction. The chapter offers two main contributions.

The technological contribution of this chapter is the first collaborative mixed reality app that allows for mixed granularity control—including environment-oriented, team-oriented, and robot-oriented control modalities. Using this app, we conducted a user study involving 28 participants and 8 real robots to study how aspects such as role assignment and modalities of interaction affect the engagement of the operators and, ultimately, the performance of the overall system.

The scientific contribution of this chapter consists in the insight that, when establishing the responsibilities of multiple operators, specialization might not be the most desirable option. This is because a certain degree of responsibility overlap across the operators might offer flexibility, resulting in an increased sense of mutual trust among operators. In addition, a more balanced workload across operators prevents the insurgence of OOTL phenomena and improve the system performance.

Chapter 5

Information Transparency

Humans and robots are envisioned to collaborate as a team [22] in complex missions, including humanitarian missions [87, 163], interplanetary exploration [81], ecosystem restoration [24, 55], mining [197], bridge inspection [175] and medical surgeries [213]. The criticality of these missions depend on an effective and efficient interaction between humans and robots. We can achieve an effective interaction with robots by making the system more transparent [196], i.e., legible and interpretable, for the human operators.

Transparency is a key property of any interface. In a transparent interface, the robots convey their state and their intentions in a way that is easy for the operators to understand and modify. Transparent interfaces offer high usability and foster increased situational awareness for the operators [17, 33, 40, 196, 223, 235]. Transparent interfaces limit or remove ambiguity, improve trust, and enhance decision-making transparency [6,32,98,112]. Lyon's models of transparency [148] and the situational awareness-based transparency (SAT) [38] model provide guidelines for an effective interaction between a human operator and the system. However, these models are designed and tested with a single operator in mind. The problem of designing a transparent interface intensifies when there are multiple human operators or multiple human-multi-robot teams. This is because the interactions among the operators become an important factor that affects the behavior and the performance of the entire system. This results in an increase of the information a human operator must process and use, affecting mental load [138, 160].

To decrease mental load, a possible approach is to limit the amount and the type of information presented to the operator. To study the effect of this idea on mental load, we consider four types of interfaces, each presenting a different amount and type of information, and each corresponding to a type of transparency.

I base these interfaces on the regions of a human eye's field of view. The field of view is the observable area a human can see through their eyes. The field of view is categorized into two regions based on its distance from the point of fixation, central and peripheral. The point of fixation is the center point of our vision. Central field of view is the part of view closest from the point of fixation and peripheral field of view is the remaining part of the view (shown in Fig. 5.1).

- No Transparency (NT): no information is available to the operator
- Central Transparency (CT): information is available in the operator's field of view
- Peripheral Transparency (PT): information is available in the boundaries of the field of view
- Mixed Transparency (MT): combination of central and peripheral transparency

In this chapter, I investigate the effects of these modes of transparency on human operator performance, awareness, task load, and trust in the system. The chapter offers two main contributions:

- I create the first mixed reality (MR) based interface for multi-human multi-robot interaction with all the mentioned modes of transparency. This interface is an extension of the mixed reality mixed granularity control interfaces presented in Sec. 3.2.1 and 4.2.2.

Figure 5.1: Central and peripheral regions of the field of view. The overlaid green region indicates the central field of view. The overlaid yellow region indicates the peripheral field of view.

- I propose the first study of the effects of transparency at the operator-level and robot-level in multi-human multi-robot interaction. The user study involved 18 participants in teams of 2, controlling 9 robots in an object transport scenario.

I organized the chapter as follows. In Sec. 5.1, I discuss related work on transparency. In Sec. 5.2, I present my system with the additional transparency features. In Sec. 5.3, I report the user study procedures and results followed by analysis in Sec. 5.4 and summarize the chapter in Sec. 5.5.

5.1 Related Work on Transparent Robot Systems

Transparency is one of the most prominent research topic in human-machine and human-robot interaction. Yet, we have only scratched the surface of the problem of making interfaces transparent. Several work exist on the relationship between humans and robots [69, 125, 219]. According to [196], transparency directly affects usability [28, 46, 177, 179, 206, 240, 249], performance [36, 42, 126, 159, 216], trust [86, 156, 198, 207] and explainability [49, 50, 79, 118, 144, 188, 195, 237]. The effect of these factors increases with the level of information provided to the operator [238, 239]. Low levels of information can negatively affect decision time, trust, situational awareness, and performance, while very high levels of information can cause a higher cognitive workload.

Ghiringhelli et al. [79] presents one such approach to graphically represent the actions of the robots using augmented reality. The paper report the interface design and focuses on the technological aspects of the interface. In contrast, Chen et al. [40] and Mercado et al. [159] report studies to test the impact of transparency on the situational awareness, trust, and workload of an operator. In their work, the studies include simulated point-mass models of the robots, lacking physical properties of mobile robots and creating a gap between results collected with simulated environment and the results collected with physical environment: *the reality gap* [103].

These works concern the scenario in which a single operator is involved as an operator of the entire system. With multiple humans interacting with multiple robots, an additional problem arises: the need for operators to share information and achieve a new form of transparency, called operator-level transparency. To the best of my knowledge, there is no study on operator-level transparency with multi-robot system, and especially none in the context of mixed granularity of control. The presented work is the first to conduct an investigation of how mixed granularity of control affects operator-level transparency.

5.2 Transparent Multi-Human Multi-Robot Interface

The multi-robot system and the interface are same as those presented in Sec. 4.2.2. I employ the simple collective transport behavior based on the finite state machine (FSM) shown in Fig. 5.3. This behavior is identical to the one presented in Sec. 3.2.4.

5.2.1 User Interface

The mixed reality interface integrates a mixed reality software development kit, Vuforia [2], and the Unity [67] game engine. The interface detects robots and movable objects by their unique fiducial markers. The robots and objects recognized by the interface are overlaid by virtual objects. The operator can manipulate the virtual objects to send commands to the robots. For example, the operator can translate a virtual object with a one-finger swipe and rotate it with a two-finger twist. It is also possible to select a team of robots by drawing a closed contour with a continuous one-finger swipe. Fig. 5.2 shows a screenshot of the default view of the application. The top-right corner shows the menu buttons to toggle the visibility of the transparency modes. The bottom-left corner shows the real-time global coordinate frame.

5.2.2 Transparency Modes

I present different modes of transparency based on the visual fields of the human eye. The interface provides a facility to switch between these transparency modes.

No Transparency (NT). The interface will block all the operator-level and robot-level information. Operators can send control commands but without access to any other feedback information.

Central Transparency (CT). The interface overlays a virtual direction pointer and a text to indicate the current task of the recognized robots (see Fig. 5.4). The direction

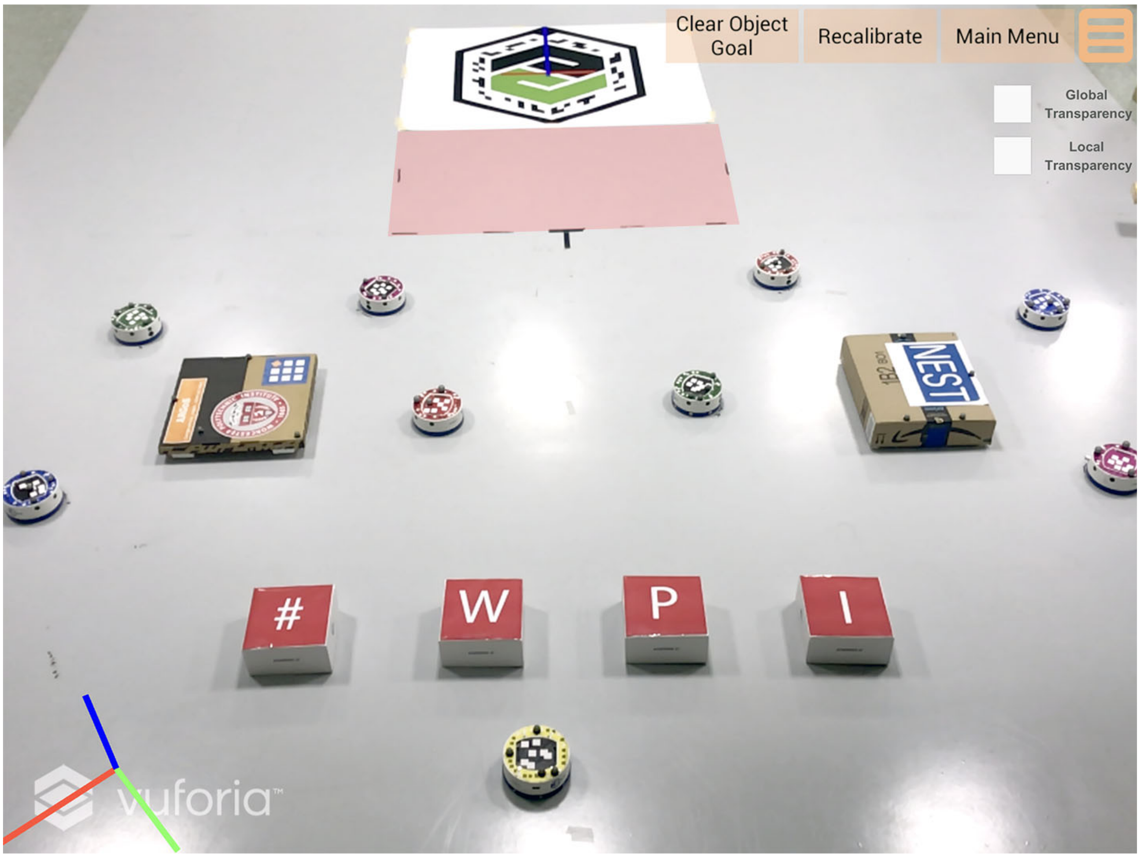


Figure 5.2: Screenshot of the MR interface running on an iPad. The overlaid black arrow indicates the origin marker for initializing the coordinate frame of the interface

pointer indicates the heading of the robot. The color of the pointers resembles the color of the unique marker to differentiate between multiple pointers when the robots are very close to each other. The interface updates the robot status every iteration and represents the current operation being performed by the robot. The displayed states are: Idle, Reach, and Error. Additionally, the interface reflects the modality changes performed by other operators making it possible to achieve a form of shared awareness. These changes in the interface are in real time, showing virtual objects being manipulated by other operators. Shared awareness helps to avoid conflicting control of the same virtual object. These features are only visible if the operator is focusing the camera on a specific recognizable robot or object, hence in the central region of the camera's field of view.

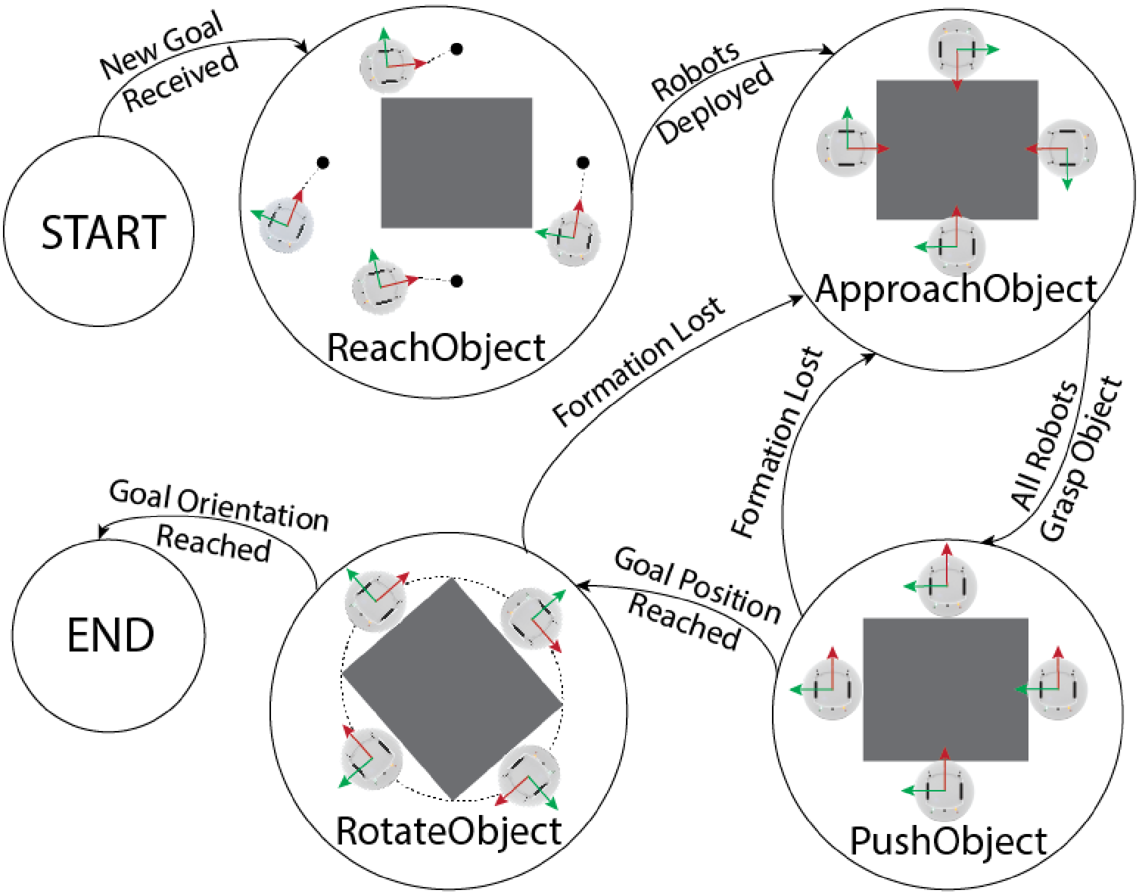


Figure 5.3: Collective transport state machine.

Peripheral Transparency (PT). The interface displays a robot panel, a text-based log, and an object panel at the edges of the screen (see Fig. 5.5). The robot panel shows all the robots present in the field. The interface highlights the icons in the panel corresponding to the robots that are moving or performing operator-defined actions. The interface shows an error, in the shape of a blinking red exclamation point, if the robot gets stuck on the ground or shows incorrect behaviour. The text-based reports displays the control actions taken by other operators. The log stores the last three actions and discards the rest. The object panel shows all the objects present in the field. The interface highlights icons in the panel that corresponds to an object manipulated by the robots. The interface gives the option of selecting an object icon to lock it for future use. The interface highlights the lock

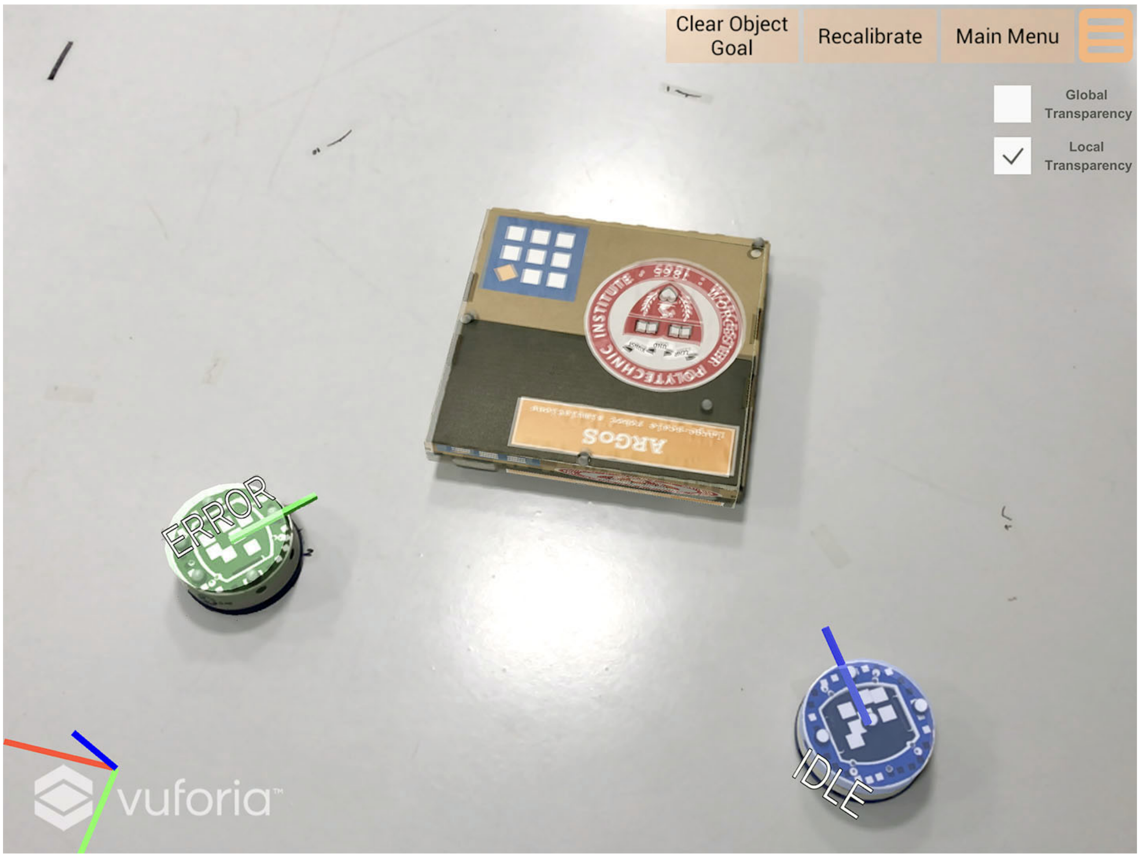


Figure 5.4: Central Transparency showing on-robot status and directional indicator.

icon next to the object icon with a blue color on selection. The operator can convey their object control intentions with this feature. The interface of other operators highlights the lock with a red icon. An operator can lock only one object at a time and the interface will remove the highlighting of the past selections.

Mixed Transparency (MT). This transparency mode is a combination of central and peripheral transparency.

Figure 5.5: Peripheral Transparency mode showing text-based lock, object panel, and robot panel (clockwise from top-left).

5.3 User Study

5.3.1 Hypotheses

The primary purpose of this chapter is to investigate the use and effects of different transparency modes on human operator's awareness, workload, trust, the quality of interaction, and performance in a multi-human multi-robot interaction system. Hence, I based the experiments on three hypotheses:

- **H$_T$1:** Mixed transparency (MT) has the best outcome as compared to other modes, in terms of situational awareness, trust, interaction score, and task load.
- **H$_T$2:** Operators prefer mixed transparency (MT) to the other modes.

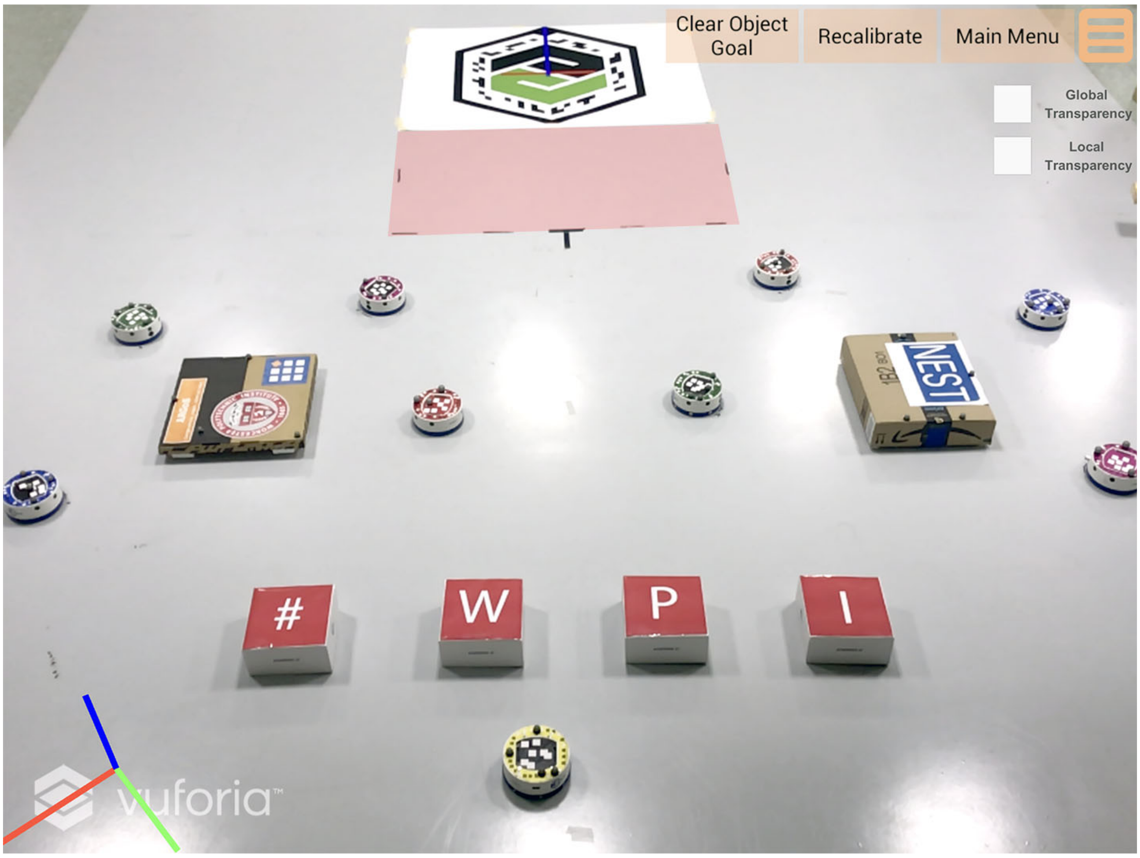


Figure 5.6: User Study experiment setup. The overlaid red region indicated the goal region.

- **H$_T$3:** Operators prefer central transparency (CT) over peripheral transparency (PT).

5.3.2 Experimental Setup

Using the interface and the hypotheses, I designed a game scenario with object transportation tasks. In this scenario, two participants had to move 6 objects (2 big and 4 small objects) from their initial position to the goal region. Big objects were worth 2 points each, and small objects were worth 1 point each. The operators had to work as a team to gain most points out of 8 in a fixed duration of 8 minutes. The operators can move the big objects using the collective transport behavior or using the robot or robot-team manipulation modality. While small objects can only be manipulated with the robot and robot-team modalities. The operators were given 9 robots to complete the game. Fig. 5.6

shows the initial positions of the robots and the objects and the goal region. All the participants performed the task 4 times with a different transparency mode (NT, CT, PT, and MT) each time.

5.3.3 Participant Sample

I recruited 18 university students (10 female, 8 male) with ages ranging from 19 to 41 years old (23.78 ± 5.08). All participants had no prior experience interacting with the system.

5.3.4 Procedures

Each session of the study had two participants and approximately took 105 minutes. After signing the consent form, I explained the task scenario and gave the participants 10 minutes to play with the system. I randomized the order of the tasks to reduce the influence of the learning curve. After each task, the participants had to answer a questionnaire.

5.3.5 Metrics

I recorded subjective and objective measures for each participant for each task. I used the following measures:

Situational Awareness. I used the Situational Awareness Rating Technique (SART) [218] on a 10-point Likert scale [143] to assess the awareness of the situation after each task.

Task Workload. I used the NASA TLX [90] scale on a 4-point Likert scale to compare the perceived workload in each task.

Trust. I used the trust questionnaire [224] on a 10-point Likert scale to compare the trust in the interface affected by each transparency mode.

Interaction. I used a custom questionnaire on a 5-point Likert scale to assess the operator-level and robot-level interaction. The interaction questionnaire had the following questions:

- Did you understand your *teammate's intentions*? Were you able to understand why your teammate was taking a certain action?
- Could you understand your *teammate's actions*? Could you understand what your teammate was doing at any particular time?
- Could you follow the *progress of the task*? While performing the tasks, were you able to gauge how much of it was pending?
- Did you understand what the *robots were doing*? At all times were you sure how and why the robots were behaving the way they did?
- Was the information provided by the interface *clear to understand* for accomplishing the task?

Performance. I used the points earned for each task as a metric to scale the performance achieved for each transparency mode.

Usability. I asked participants to select the features (Log, Robot Panel, Object Panel, and On-Robot Status) they used during the study. Additionally, I asked them to rank the transparency modes from 1 to 4, 1 being the highest rank.

5.3.6 Results

Table 5.1 shows the summarized results for all the subjective scales and the objective performance. I used the Friedman test [75] to analyze the data and to assess the significance among different tasks. I formed ranking based on the mean ranks for all the attributes that showed statistical significance ($p < 0.05$) or marginal significance ($p < 0.10$).

Table 5.1: Results with relationships between transparency modes. The relationship are based on mean ranks obtained through Friedman Test. The symbol * denotes significant difference ($p < 0.05$) and the symbol ** denotes marginally significant difference ($p < 0.10$). The symbol $^-$ denotes negative scales and lower ranking is a good ranking.

Attributes	**Relationship**	$\chi^2(3)$	p-**value**
SART SUBJECTIVE SCALE			
Instability of Situation$^-$	not significant	4.192	0.241
Complexity of Situation$^-$	NT>MT>PT>CT**	6.435	0.092
Variability of Situation$^-$	not significant	4.192	0.241
Arousal	NT>MT>PT>CT**	7.093	0.069
Concentration of Attention	not significant	4.664	0.198
Spare Mental Capacity	not significant	3.526	0.317
Information Quantity	MT>CT=PT>NT*	16.160	0.001
Information Quality	MT>CT>PT>NT*	11.351	0.010
Familiarity with Situation	not significant	1.911	0.591
NASA TLX SUBJECTIVE SCALE			
Mental Demand$^-$	not significant	6.169	0.104
Physical Demand$^-$	not significant	3.526	0.317
Temporal Demand$^-$	not significant	0.564	0.903
Performance	not significant	4.573	0.206
Effort$^-$	NT>PT>CT>MT*	9.203	0.027
Frustration$^-$	NT>CT>MT>PT*	9.205	0.027
TRUST SUBJECTIVE SCALE			
Competence	not significant	3.703	0.295
Predictability	PT>CT>MT>NT**	6.359	0.095
Reliability	not significant	4.338	0.227
Faith	not significant	1.891	0.595
Overall Trust	PT>MT>CT=NT*	12.607	0.005
Accuracy	PT>MT=CT>NT*	12.214	0.007
INTERACTION SUBJECTIVE SCALE			
Teammate's Intent	MT>PT>CT>NT*	23.976	< 0.001
Teammate's Action	MT>PT=CT>NT*	22.511	< 0.001
Task Progress	MT>CT>PT>NT*	25.619	< 0.001
Robot Status	CT>PT>MT>NT*	13.608	0.003
Information Clarity	CT>PT>MT>NT*	12.078	0.007
PERFORMANCE OBJECTIVE SCALE			
Points Scored	not significant	5.554	0.135

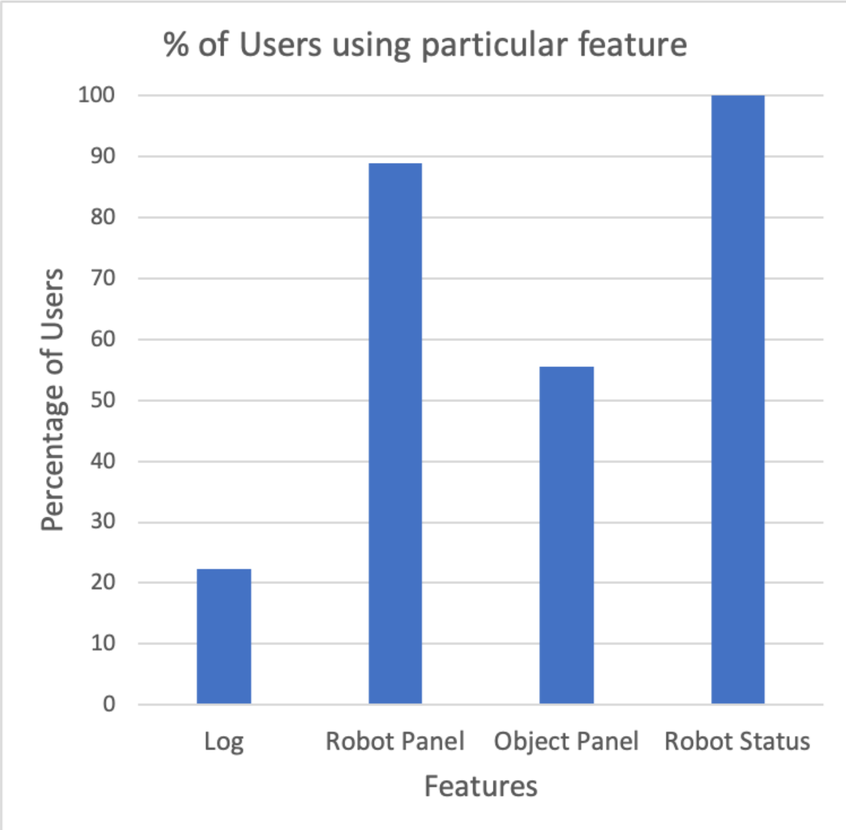


Figure 5.7: Feature Usability.

Table 5.2: Ranking scores based on the Borda count. The gray cells indicate the leading scenario for each type of ranking.

Borda Count	NT	CT	PT	MT
Based on Collected Data Ranking (Table 5.1)	17.5	40	39	43.5
Based on Preference Data Ranking (Fig. 5.8)	18	46	45	72

Fig. 5.7 shows the percentage of operators using a particular feature. Fig. 5.8 shows the percentage of people ranking task based on their choice.

I used the Borda count [20] method for calculating the overall ranking of the collected data and transparency mode usability data. I inverted the ranking of the negative scales when calculating the Borda count scores. Table 5.2 shows the results of the Borda count for each category.

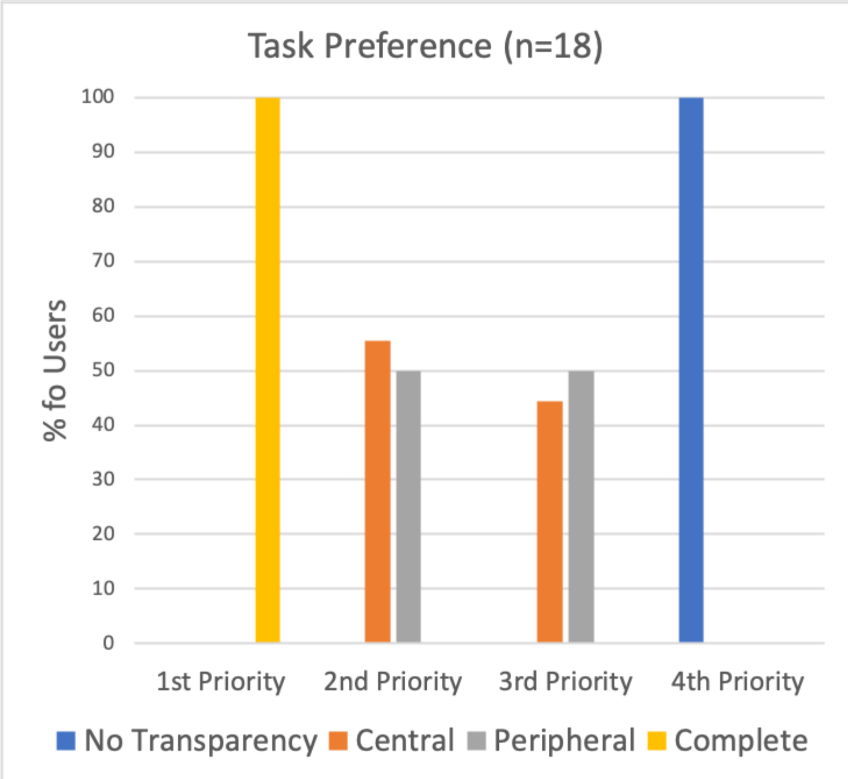


Figure 5.8: Task Preference.

5.4 Analysis and Discussion

Table 5.2 shows mixed transparency (MT) as the overall winner and people's choice winner, in accordance with hypotheses $\mathbf{H}_T\mathbf{1}$ and $\mathbf{H}_T\mathbf{2}$. The data suggests that central transparency is better than peripheral transparency, confirming my hypothesis $\mathbf{H}_T\mathbf{3}$.

Mixed Transparency. This mode is the overall best choice for operators. The data suggests that this mode has the best information quality and quantity. The operators could choose between the information they wanted to use from the central transparency (CT) and peripheral transparency (PT) modes. However, operators experienced more complexity and arousal due to the increased availability of information. The usability test suggested this mode as the best for obtaining teammates information; intent and action. This justifies the fact that mixed transparency is the first choice.

Central Transparency. This mode has the least complexity and arousal, as operators got information at the center of the screen and they could focus on the information. The operators preferred to use on-robot status as compared to the robot panel. Thus they experienced better information quality and clarity as compared to peripheral transparency (PT). This mode is the best for understanding the status and behavior of the robots. 10 operators preferred this mode over peripheral transparency, making it the second choice overall.

Peripheral Transparency. The operators found the information displayed at the border of the interface screen hard to parse and access. This led to increased effort, complexity, and arousal when compared with the central transparency interface. However, as the information was available on-demand and not constantly displayed in the field of view, the perceived frustration was the least. In this mode, operators preferred the visual panels over the text-based log. Additionally, the operators preferred this mode over central transparency to stay aware of the teammate's intention.

The experiments did not report a substantial difference in performance across transparency modes. We hypothesize that this lack of difference is due to a learning effect across the four runs each team had to perform. We could not avoid this learning effect through randomization of the transparency modes. Fig. 5.9 shows the performance in each task and Fig. 5.10 shows the increase in performance in order of the performed task (learning effect). However, the task performance dropped or stayed same for groups who used no transparency mode after using other transparency modes.

5.5 Chapter Summary

In this chapter, I studied the effects of different transparency modes in a multi-human multi-robot interaction. I classified the transparency based on the region of the field of

Figure 5.9: Task performance for each transparency mode.

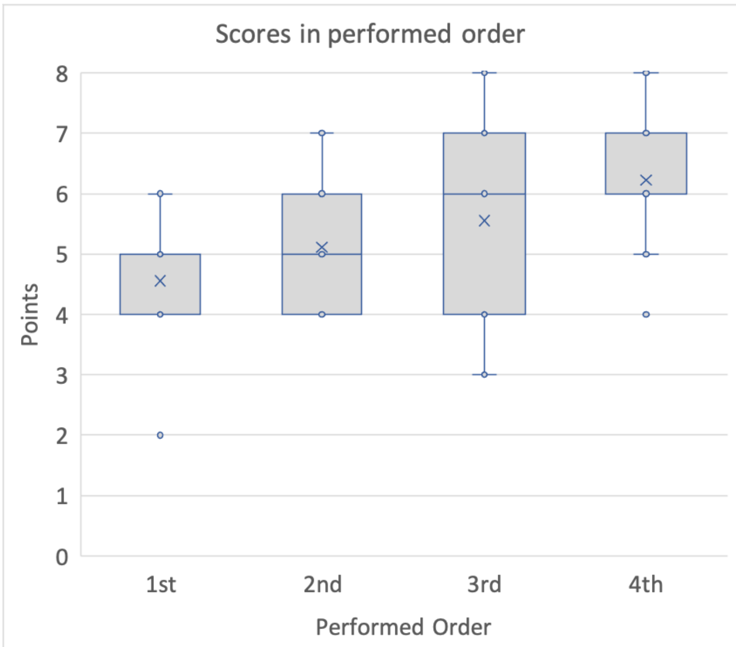


Figure 5.10: Learning effect in the user study.

view (central and peripheral transparency) and a combination of them. I demonstrated the design of the first mixed reality interface that supports different modes of transparency and provides both operator-level and robot-level information.

I performed a user study with 18 operators to test and validate the effects of these modes of transparency on an operator's awareness, workload, trust, and interaction. I predicted mixed transparency to outperform other modes in terms of overall effect and usability. The results of the study suggested the same and operators chose mixed transparency as the best mode to use. I also compared central transparency with peripheral transparency. Although there was a close contest, more operators preferred central transparency (55.55%) over peripheral transparency (45.45%).

Chapter 6

Cooperation among Operators

Communication between humans and robots has been a field of key interest since the conceptualization of Asimov's three laws of robotics [8]. Ever since, humans have been expanding the boundaries of robotics towards the vision of a shared work space [22, 77]. The next step of this vision is to include more than one human in the system, adding a layer of inter-human communication. Although inter-human communication has been studied extensively [220], it has sparsely been investigated with robots involved in the chain of communication.

Communication between humans can be direct, indirect, or a mix of both. Direct communication is an explicit form of information exchange such as verbal communication or communication through gestures. Indirect communication is an implicit form of information exchange encoded through mechanisms such as social cues and body language [95].

However, the specific communication mechanisms are likely to be different from purely inter-human communication when robots become part of the system [157, 200].

Direct communication can be a mix of verbal communication and gesture (non-verbal pointing, nodding and/or facial expressions) communication. Through direct communication, operators can explicitly declare their actions and intentions and expect an explicit acknowledgement. Operators can also guide each other or request help from others in case of system failures.

Indirect communication occurs by making the operator-level activities transparent [17, 23, 38, 148, 196, 235]. An operator can monitor other operators' actions to understand their intentions and predict future actions. The operator help others by observing their actions and robots to predict the chance of failure based on their current actions.

There has been little attention in research with the context on inter-human communication in a multi-human multi-robot interaction. In this chapter, I explore the effects of different types of communication on operator-level interaction, task awareness, trust, and workload in a collaborative task. I categorize communication as: no communication (NC), direct communication (DC), indirect communication (IC) and mixed communication (MC). The operators verbally communicate as a form of direct communication and use the transparent interface to engage in indirect communication. Mixed communication is an combination of direct and indirect communication. I investigate the effects of types of communication through a study with 18 operators, in teams of 2, and 9 robots involved in an object transport scenario.

The chapter is organized as follows. In Sec. 6.1 I discuss background literature on human-robot communication. In Sec. 6.2 I present the design of my interface with transparency features. In Sec. 6.3 I detail the user study, with a discussion of the results in Sec. 6.4. I summarize the chapter in Sec. 6.5.

6.1 Related Work on Human Communication

Communication is an exchange of information, either direct or indirect, between the constituents of the interaction. There has been a substantial development in verbal and non-verbal communication between humans and robots [157, 200]. Humans can verbally communicate with robots using natural language [19] to explicitly convey their intention. Humans can non-verbally communicate through social cues [199], facial expressions [146] and eye gaze [3, 23] to implicitly convey their intentions. In addition to communication between a human and a robot, humans can also communicate with multiple robots at once, using body and hand gestures [5, 167, 169], tactile interfaces [128, 178], hand-held devices [57, 182] and haptic devices [208].

Lakhmani et al. [126] presented a method for direct communication between an operator and a robot. The authors classified the communication in *directional* and *bidirectional*. In directional communication only the robot can send information to the operator. In bidirectional communication, both operator and robot can send information to each other. The authors reported that the operator performed better with directional communication as compared to bidirectional communication. This work, however, is limited to direct communication between a human and a robot, and does not consider indirect forms of communication.

Che et al. [34], compare the effects of direct and indirect communication between a human and a robot in a navigation task. In this work, the human acts as a bystander and the robot has to navigate around the human. The robot can either indirectly predict the human's direction of movement and navigate around, or can directly notify the human about its intentions of moving in a direction. The authors reported that the combination of indirect and direct communication positively impacts the humans performance and trust. The study, however, is limited to a human bystander sharing an environment with a robot, and is not applicable to a human operator responsible for interacting with the robot.

To the best of my knowledge, there is no work that studies communication between human operators in a multi-human multi-robot interaction and its effects on the interaction between human operators.

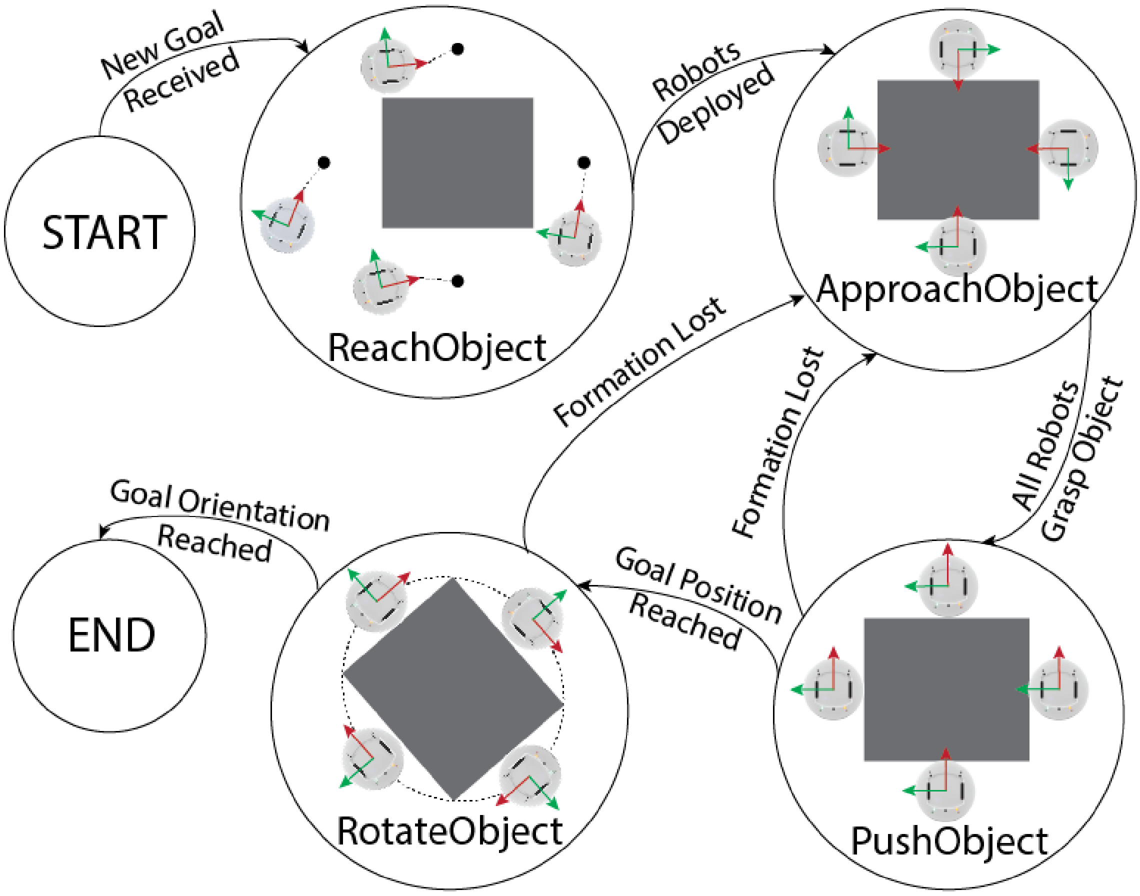


Figure 6.1: Collective transport state machine.

6.2 Transparent Multi-Human Multi-Robot Interface

The multi-robot system and the interface are same as those presented in Sec. 4.2.2. I use the finite state machine based collective transport behaviour. Fig. 6.1 shows the state machine with state transition conditions. This behavior is identical to the one presented in Sec. 3.2.4.

6.2.1 Transparency

I use the transparency features of the interface, a combination of central transparency and peripheral transparency (explained in Chapter 5), to provide indirect communication

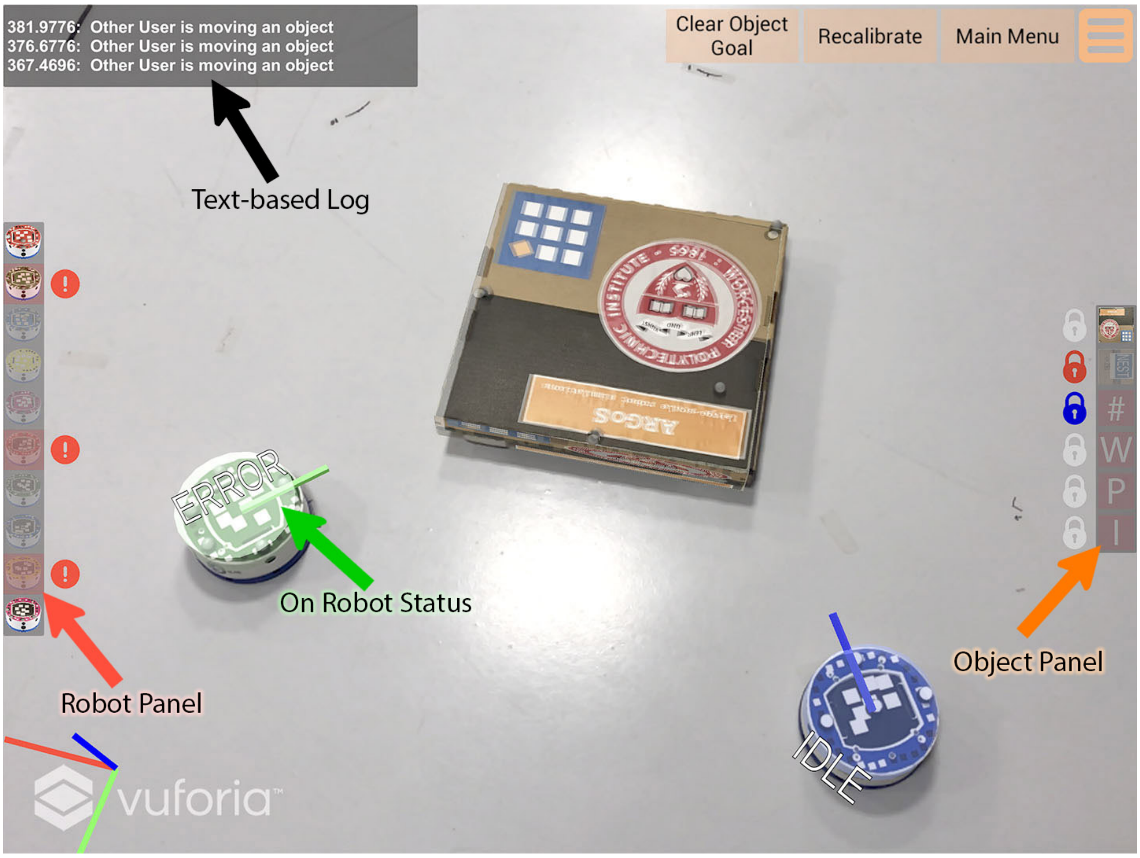


Figure 6.2: Transparency features in the mixed reality interface. The overlaid black arrow indicate the text-based log. The overlaid red arrow indicates the Robot Panel. The overlaid green arrow indicates the on-robot status. The overlaid orange arrow indicates the object panel.

between operators. Through these features, an operator can monitor other operators' actions, intentions, and system failures. The interface reflects the operators' actions through a text-based log, shared awareness, the robot panel , the robot status, and the object panel (shown in Fig. 6.2).

Text-based Log. The text-based log reports the actions taken by other operators. The interface updates the log every time other operators manipulate any virtual container. The log stores the last three actions and discards the rest.

Shared Awareness. The interface synchronously changes the positions of the virtual containers in the mixed reality view every time an operator manipulates them, hence sharing awareness. This includes object manipulation, robot manipulation, and robot-team selection and manipulation.

Robot Panel and On-Robot Status. The interface highlights the robot icons and changes on-robot state corresponding to the robots that are moving or performing operator-defined actions. This feature helps other operators observe and avoid the use of robots that are performing a certain operation. The panel displays a blinking red exclamation point and on-robot status displays an error if a robot is stuck or behaves incorrectly. This feature allows operators to instruct or help others in case of system failures.

Object Panel. The interface highlights the object icon corresponding to the object being moved by the robots. Additionally, the interface offers the option of selecting an object icon to lock it for future use. An operator can lock the object by tapping the lock icon. This will change the color of the lock to blue, signifying the selection. An operator can select only one object at a time, and the interface will remove the past highlights. The interface of the other operators highlights the lock with a red icon. This reflects the locking of other operators by highlighting the lock with a red color.

6.3 User Study

6.3.1 Hypotheses

This study investigates the effects of direct and indirect communication on multi-human multi-robot interaction. Hence, I base the experiments on three hypotheses:

- **H$_C$1:** Mixed communication (MC) has the best outcome as compared to the other modes, in terms of situational awareness, trust, interaction score and task load.

- **H$_C$2:** Operators prefer mixed communication (MC) to the other modes.

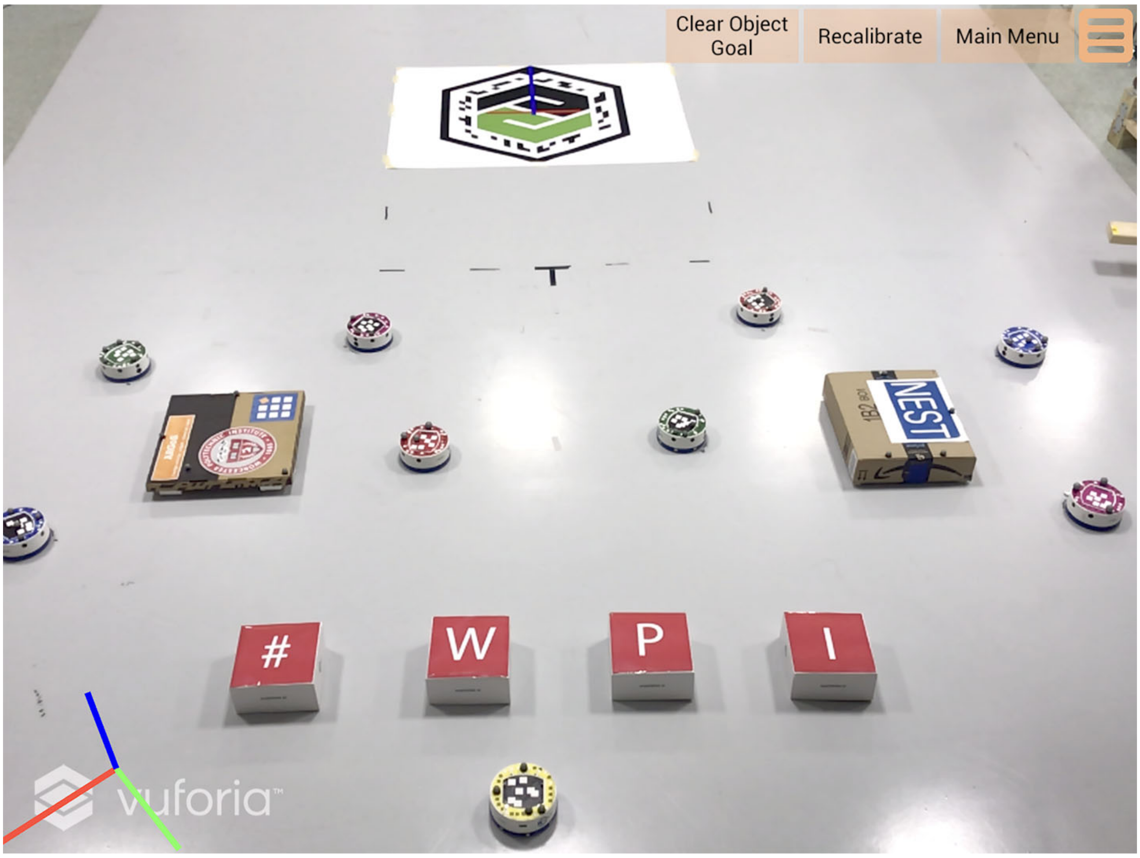


Figure 6.3: User study experiment setup.

- **H$_C$3:** Operators prefer direct communication (DC) over indirect communication (IC).

6.3.2 Experimental Setup

I designed a game scenario with object transportation tasks for 6 objects (2 big objects and 4 small objects). The operators receive points, associated with each object, upon completing the transportation of an object. The big objects were worth 2 points each and small objects were 1 point each, thus 8 points in total. The operators, in teams of 2, had to interact with robots for transporting these objects from their initial position to a goal region in a duration of maximum 8 minutes. Operators can manipulate big objects with either object control, robot control, or robot-team control modality, while small objects can only be manipulated with the robot and robot-team modalities. The operators were given 9 robots to complete the game. Fig. 6.3 shows the initial positions of the objects and the robots. All the participants had to perform the task 4 times with a different mode of communication. The communication modes are explained as follows:

No Communication (NC): Operators cannot communicate directly or indirectly while performing the task.

Direct Communication (DC): Operators can communicate verbally and non-verbally while performing the task. They can directly ask for help or provide help through direct communication.

Indirect Communication (IC): Operators can communicate indirectly through the transparency features of the interface. Operators can understand the intentions and actions of the teammate through the transparent features in the mixed reality interface.

Mixed Communication (MC): Operators can communicate directly and indirectly while performing the task.

6.3.3 Participant Sample

I recruited 18 students from the university (11 male, 7 females) with age ranging from 20 to 30 years old ($M = 24.17$, $SD = 2.68$). No participant had any prior experience of interacting with the interface.

6.3.4 Procedures

Each study session had two participants and took 105 minutes approximately. I explained the study to the participants after signing a consent form and gave 10 minutes to play with the interface. I randomized the order of the tasks to reduce the influence of the learning effect.

6.3.5 Metrics

I recorded subjective measures from the operators and objective measures from the task for each trial. I used the following scales as metrics:

Situational Awareness. I measured situational awareness using the Situational Awareness Rating Technique (SART) [218] on a 4-point Likert scale [143] to compare the awareness of the situation after each task.

Task Workload. I used the NASA TLX [90] scale on a 4-point Likert scale to compare the perceived workload in each task.

Trust. I employed the trust questionnaire [224] on a 4-point Likert scale to compare the trust in the interface affected by each transparency mode.

Interaction. I used a custom questionnaire on a 5-point Likert scale to assess the effects of communication. The interaction questionnaire had the following questions:

- Did you understand your *teammate's intentions*? Were you able to understand why your teammate was taking a certain action?

- Could you understand your *teammate's actions*? Could you understand what your teammate was doing at any particular time?

- Could you follow the *progress of the task*? While performing the tasks, were you able to gauge how much of it was pending?

- Did you understand what the *robots were doing*? At all times, were you sure how and why the robots were behaving the way they did?

- Was the information provided by the interface *clear to understand*?

Performance. I measured the performance achieved for each communication task by using the points earned for each task as a metric to quantify .

Usability. I asked participants to select the features (Log, Robot Panel, Object Panel, and On-Robot Status) they used during the study. Additionally, I asked them to rank communication modes from 1 to 4, 1 being the highest rank.

6.3.6 Results

I analyzed data using the Friedman test [75] and summarized the results based on the significance and the mean ranks. Table 6.1 shows the summarized results along with relationship ranking between the communication modes. I formed the rankings for each scale using the mean ranks of the Friedman test. I categorized the relationship with a significance of $p < 0.05$ and a marginal significance of $p < 0.10$.

Fig. 6.4 shows the usability results, i.e., the percentage of operators that used a particular feature for completing a specific task. Fig. 6.5 shows the communication mode choice ranking, i.e., the percentage of operators and the priority of their preference.

I used the Borda count [20] to quantify all the derived rankings based on data and preference to find an overall winner. I inverted the ranking of the negative scales when calculating the Borda count. Table 6.2 shows the Borda count results.

6.4 Analysis and Discussion

Table 6.1 shows that mixed communication (MC) has the best information quality and quantity, leading to the best awareness and trust. However, with more information, the operators experienced greater instability of situation and variability of situation (see *SART Subjective Scale* section of Table 6.1). Operators found mixed communication as the best choice through both data and preference (see Table 6.2), hence conforming the hypotheses $\mathbf{H}_C\mathbf{1}$ and $\mathbf{H}_C\mathbf{2}$.

Table 6.1: Results with relationships between communication modes. The relationship are based on mean ranks obtained through Friedman Test. The symbol * denotes significant difference ($p < 0.05$) and the symbol ** denotes marginally significant difference ($p < 0.10$). The symbol $^-$ denotes negative scales and lower ranking is a good ranking.

Attributes	**Relationship**	$\chi^2(3)$	p**-value**
SART SUBJECTIVE SCALE			
Instability of Situation$^-$	NC>IC>DC>MC*	9.000	0.029
Complexity of Situation$^-$	not significant	2.324	0.508
Variability of Situation$^-$	IC>NC>MC>DC*	9.303	0.026
Arousal	IC>NC>MC>DC*	6.371	0.095
Concentration of Attention	IC>NC>DC>MC*	17.149	0.001
Spare Mental Capacity	not significant	5.858	0.119
Information Quantity	MC>DC>IC>NC*	15.075	0.002
Information Quality	MC>DC>IC>NC*	15.005	0.002
Familiarity with Situation	not significant	6.468	0.101
NASA TLX SUBJECTIVE SCALE			
Mental Demand$^-$	not significant	2.226	0.527
Physical Demand$^-$	not significant	2.165	0.539
Temporal Demand$^-$	not significant	3.432	0.330
Performance	not significant	0.412	0.938
Effort$^-$	not significant	1.450	0.694
Frustration$^-$	not significant	4.454	0.216
TRUST SUBJECTIVE SCALE			
Competence	not significant	4.740	0.192
Predictability	MC>IC>DC>NC*	10.626	0.014
Reliability	MC>IC>DC>NC*	8.443	0.038
Faith	MC>IC>DC>NC*	9.451	0.024
Overall Trust	MC>IC>DC>NC**	6.633	0.085
Accuracy	not significant	1.891	0.595
INTERACTION SUBJECTIVE SCALE			
Teammate's Intent	DC>MC>IC>NC*	19.610	0.000
Teammate's Action	MC>DC>IC>NC*	13.810	0.003
Task Progress	MC>DC>IC>NC*	9.686	0.021
Robot Status	not significant	0.811	0.847
Information Clarity	not significant	5.625	0.131
PERFORMANCE OBJECTIVE SCALE			
Points Scored	not significant	0.808	0.848

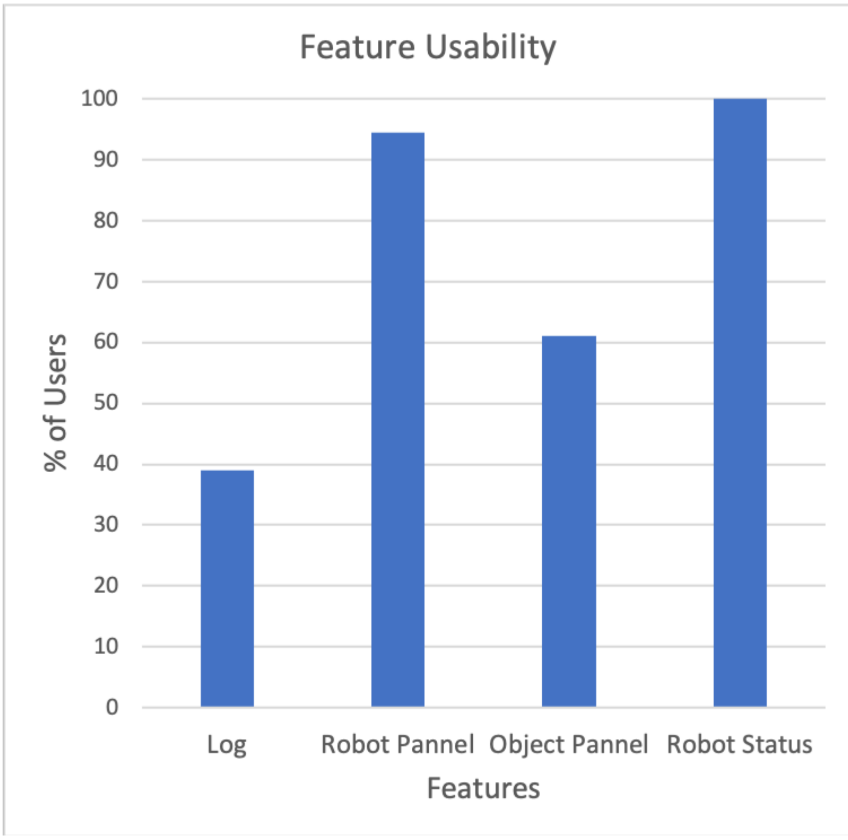


Figure 6.4: Feature Usability.

Table 6.2: Ranking scores based on the Borda count. The gray cells indicate the leading scenario for each type of ranking.

Borda Count	NC	DC	IC	MC
Based on Collected Data Ranking (Table 6.1)	18	34	33	45
Based on Preference Data Ranking (Fig. 6.5)	18	49	41	72

Direct communication (DC), compared to indirect communication (IC), had better information quality and quantity, leading to a better awareness. However, similar to the mixed communication, the operators experienced greater instability of situation and variability of situation. Although trust is higher in indirect communication, operators prefer direct communication. The Borda count for preference data shows the precedence of direct communication over indirect communication, supporting the hypothesis $\mathbf{H}_C\mathbf{3}$.

However, in the absence of direct communication, the operators concentrated more on

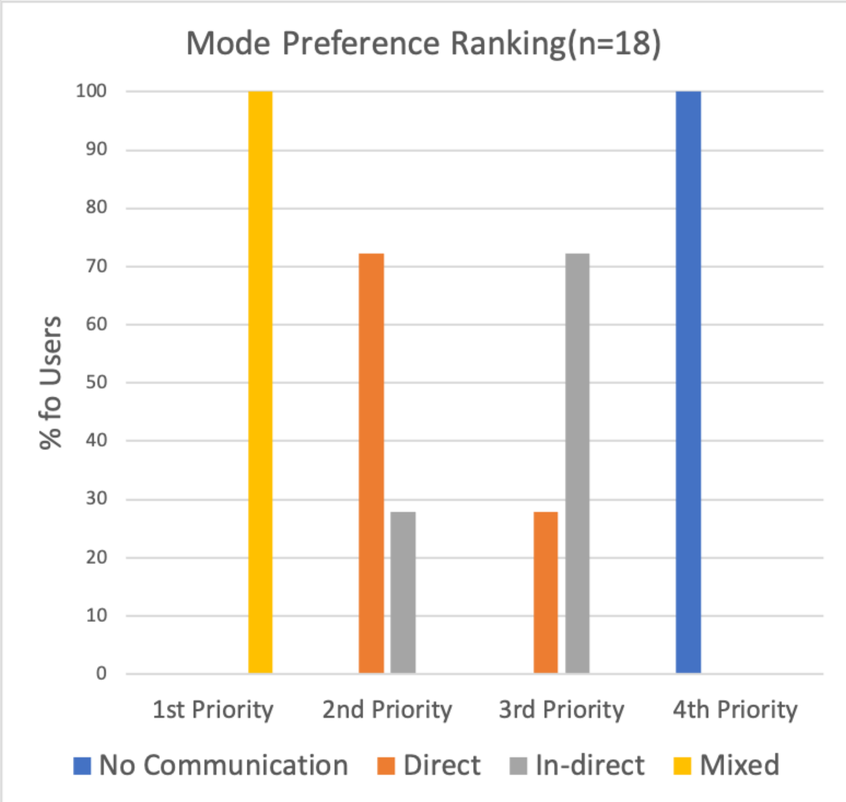


Figure 6.5: Task Preference.

the task, leading to a higher level of arousal and better trust (see *Trust Subjective Scale* section of Table 6.1). Although indirect communication provides more diverse and more visually augmented information, operators relied on direct communication when working as a team. I also observed operators directly communicating either at the start of the task, to define a strategy, or nearing the end of the task, coordinate the last part of the task. One reason can be the familiarity of information. Humans are more familiar with direct communication. The operators were new to the transparency-based information and were unable to use it as effectively as that from direct communication. This raises another research question and a potential future study to compare the effects of mixed communication on novice operators and on expert operators.

The experiments did not report a substantial difference in performance across communi-

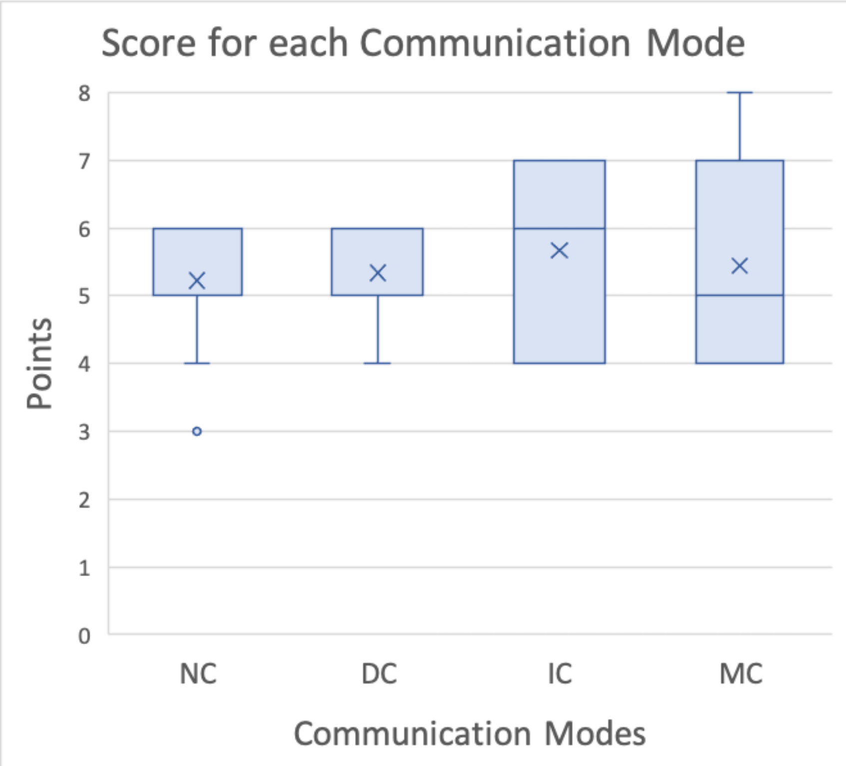


Figure 6.6: Task performance for each communication mode.

cation modes. However, I hypothesize that this lack of difference is because of the learning effect across the trials each team had to perform. Fig. 6.6 represent the points earned for each communication mode and Fig. 6.7 shows the learning effects as the increase in objective performance in order of the performed task.

6.5 Chapter Summary

In this work, I studied different communication methods between human operators in a multi-human multi-robot interaction. I characterized communication as either direct, indirect, or a mix of both. Operators could engage in direct communication by verbal exchange of information about themselves, the robots, or the task. Operators could engage in indirect communication by using transparency-based information exchange. Through

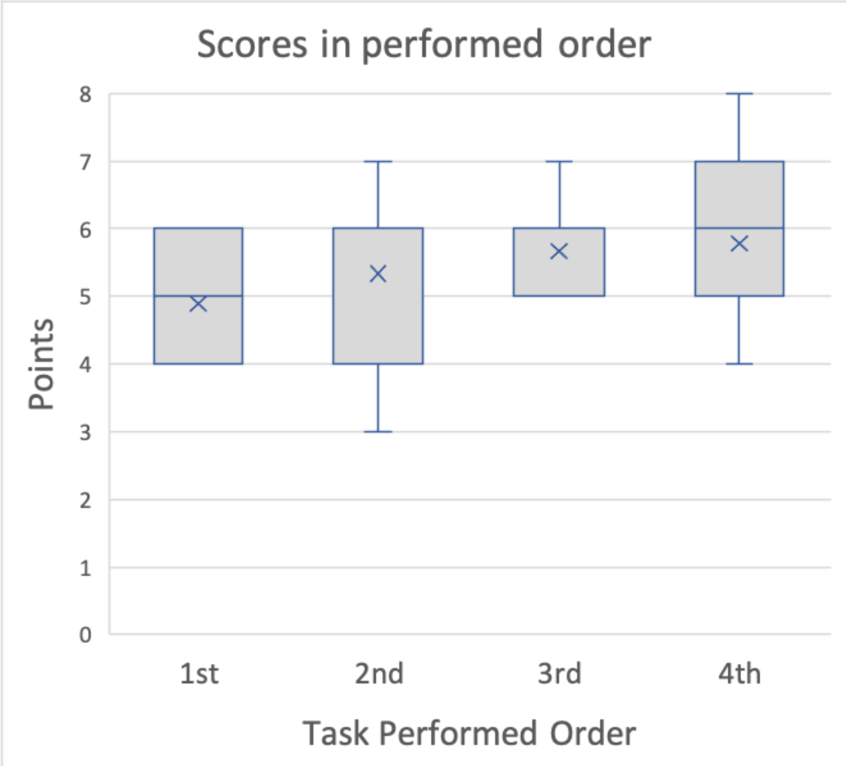


Figure 6.7: Learning effect in the user study.

transparency, operators could broadcast their intentions, and actions while monitoring their teammates.

I performed a user study to determine the effects of different communication modes on an operator's awareness, trust, workload, and usability. The results indicated mixed communication as the best in terms of subjective metrics and usability. The results also showed the precedence of direct communication over indirect communication. Operators preferred verbally communicated information over transparency-based information for effective teamwork.

Chapter 7

Remote Interaction

Multi-robot systems promise solutions for missions in which direct human involvement is either impossible or undesirable, such as search-and-rescue, firefighting, planetary exploration, and ocean restoration [162]. When multiple robots are deployed to perform complex missions, autonomy is only part of the picture. Along with autonomy, it is equally important for human operators to monitor and affect the behavior of the robots. This creates the issue of designing effective solutions for remote interaction between humans and multiple robots.

While a significant body of work exists in remote interaction involving single humans and one or more robots, the scenario in which *multiple* humans interact with multiple robots has received little attention. In this chapter, we argue that it will be common for multiple humans to cooperate in the supervision of multiple robots. First, the amount of information generated by the robots is likely to exceed the span of apprehension of any individual operator [160], even when considering highly skilled ones such as video gamers. Cooperation among human operators would make monitoring more efficient. Second, the involvement of multiple humans allows for improved flexibility in robot control and task assignment, an important advantage in complex operations.

However, the involvement of multiple humans comes with old and new challenges.

Among the old, we highlight the need for *information transparency*, which is the ability of the interface-robot system to convey useful data for the operators to understand and modify the status of the robots [17, 33, 40, 196, 223, 235]. Multiple operators also create the new challenge of conveying intentions and actions to other operators, i.e., effective *inter-human communication*, for better cooperation and conflict mitigation [220]. Inter-human communication can be either *direct* or *indirect*. Direct communication includes verbal and non-verbal communication (e.g., gestures) [95]. Indirect communication is mediated through the remote interface (e.g., a graphical user interface on a laptop or tablet). Effective indirect communication requires *inter-operator transparency*, which pushes for interface designs that make it simple for operators far away from each other to exchange information on their intentions and plans [17, 23, 38, 148, 196, 235].

In this chapter, I explore the design space of remote interfaces for multi-human multi-robot interaction. I study the role of direct and indirect communication among operators, and investigate how to achieve high levels of information and inter-operator transparency through several variants of my interface. The result of this work is a set of recommendations on which design elements contribute to making a remote interface effective. This part of the study builds upon Chapters 5 and 6 in which I investigated transparency and inter-human communication on the performance of human operators in *proximal interaction*. Proximal interaction occurs when humans and robots share the same environment.

Remote interaction allows us to study another important aspect—the role of *information loss*. In this chapter, I consider information loss as a decrease in the frequency of the visual information presented to the operators. I measure information loss as the time interval, measured in seconds, between the delivery of consecutive video frames (the inverse of frames per second). Packet loss, bandwidth limitations, and geographical distance between the locations of the operators and the robots act as causal factors for information loss. Information loss leads to degraded operator performance, lack of awareness and trust, and increase in cognitive workload [62].

The last factor I consider in my study is that, in presence of non-ideal communication, it is also likely that the operators experience *heterogeneous* levels of information loss, causing a disparity in workload and situational awareness across operators.

The main contributions of this chapter can be summarized as follows:

- I provide an extensive investigation of the design space of remote interfaces for multi-human multi-robot interaction. I consider factors such as direct and indirect communication, information and inter-operator transparency, and homogeneous and heterogeneous information loss.

- I compile a set of design recommendations validated through a user study that included 48 participants. I implemented a highly configurable remote interface that incorporates these recommendations and enables future studies of this kind.

This chapter is organized as follows. I discuss related literature on remote human-robot interaction in Sec. 7.1. In Sec. 7.2, I discuss the design of my configurable remote interface. I report the results of the user study in ideal conditions in Sec. 7.3. I then introduce different types of information loss and report the results of a dedicated user study in Sec. 7.4. I summarize the contributions and outline directions for future work in Sec. 7.5.

7.1 Related Work on Remote Interaction

Remote robot control and manipulations has been a field of interest since Goertz and Thompson laid the foundation of modern tele-operation [80]. The field has mostly focused manipulators [94, 109, 141, 142, 225] rather than on mobile robots. This body of research has contributed advancements in tele-presence [58, 70, 119, 120], tele-robotics [171, 189], tele-operation [96, 105, 149, 154, 202], and tele-surgery [52, 184, 209]. This research has focused on identifying suitable interfaces and improving their usability [68, 104, 124, 147, 166, 191, 194, 234], as well as proposing novel control architectures for these interfaces [45, 59, 129, 134]. Chen *et al.* [39] categorize existing research according to the factors that affect remote control of robots. These factors are field of view, system orientation, camera viewpoints, depth perception, degraded video quality, time delay, and camera motion. Building upon this work, Feth *et al.* [71] and Kim *et al.* [116, 117] present a shared control framework to allow multiple operators to interact with manipulators. Lee *et al.* [60] extend these shared control frameworks to study the impact of information delay on the performance of human operators. In their work, the authors incorporate a passivity-based controller to counteract the negative effects of information delay on operator's performance. These works are limited to interface design for remote interaction with industrial manipulators, and their findings may not be applicable to remote interface for manipulating numerous mobile robots. To the best of my knowledge, the study is the first study that investigates the impact of transparency and inter-human communication on a multi-human multi-robot interaction.

Loss of information has been recognized as a key factor in the performance and engagement of human operators [37, 39, 53, 62, 127, 150, 155, 190, 212, 231]. Research suggests that the effect of information loss and the ability to handle the loss may vary according to the tasks and the interface to interact with the system. To overcome the degradation in performance, there are three methods to mitigate the effects of loss on the performance of human operators. These methods are adopting passivity-based control methods [45, 94, 109, 135, 225], predictive displays [11, 27, 48, 51, 114, 115, 172, 192, 211] and higher granularity of control [9, 122, 182]. However, these studies are limited to the scenario in which a single operator interacts with one of more robots. The study furthers this line of research by providing an extensive investigation of the factors that affect the design of remote interfaces for *multi*-human multi-robot interaction in presence of information loss.

7.2 System Design

In this section, I present the main features of the remote interface and the behavior of the robots. At its essence, the interface is a web-based client-server architecture. The server runs ARGoS [186], a fast multi-robot simulator, on a node offered by Amazon Web Services[1]. The server is implemented as a visualization plugin that accepts multiple connections from the clients. The client side is a web application implemented with Node.js[2] and WebGL[3] which offers similar features with respect to the original graphical visualization of ARGoS. A diagram of the client-server architecture is reported in Fig. 7.1 and a screenshot of the web interface is shown in Fig. 7.2. The source code of the system is available online as open source software.[4]

The process starts when a user performs a command on the client. The web interface allows the user to operate at multiple levels of granularity. In Chapter 3, I found that mixed granularity of control offers superior usability in complex missions that require both navigation and environment modification. Similarly to [183], in this chapter I focus on a collective transport scenario due to the compositional nature that this kind of task presents — collective transport combines navigation, task allocation, and object manipulation. The interface is therefore designed for this scenario and it mirrors many of the features I presented in [183]. It is important to highlight, however, that the remote interface presented here is a completely new artifact based on a different technology: in fact, the work in [183] studied *proximal* interactions with a *touch-based* interface.

[1] https://aws.amazon.com/
[2] https://nodejs.org/
[3] https://get.webgl.org/
[4] https://github.com/NESTLab/argos3-webviz

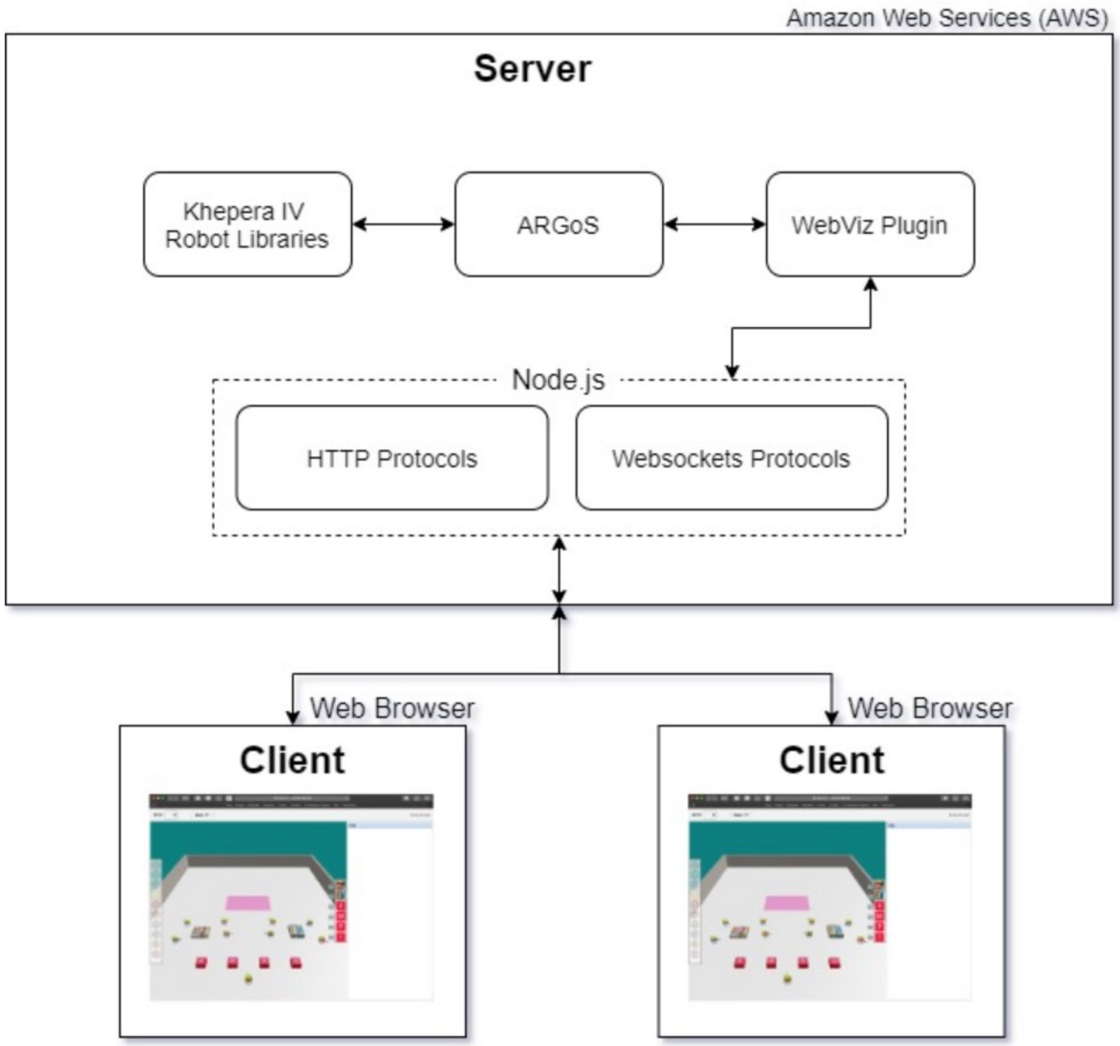


Figure 7.1: System overview.

7.2.1 Collective Transport

I employ a collective transport behavior based on the finite state machine shown in Fig. 7.3. The behavior is identical to the one discussed in Chapter 3.

7.2.2 User Interface

Object Manipulation. Object manipulation is triggered when an operator selects an object with a left click. The goal position always requires a right click, and the interface

Figure 7.2: Screenshot of the interface running on an internet browser.

overlays the selected object with a transparent bounding box. The operator can also define the goal position for multiple objects. In this case, the robots autonomously distributed across the objects and transport them using the collective transport behavior. If two or more operators manipulate the same object, the interface keeps the position specified by the last operator. Fig. 7.4a shows a selected object overlaid with a bounding box. Fig. 7.4b illustrates how the goal position is visualized. The desired position and orientation of the object is conveyed by the interface as shown in Fig. 7.4c and 7.4d.

Robot Manipulation. Robot manipulation starts with an operator selecting a robot with a left click. The goal position is assigned using a right click. The interface overlays the selected robot with a transparent bounding box convey the current selection. The operator can define the goal position for multiple robots at once. If the robot is performing the collective transport behavior during this request, other robots in the collective transport

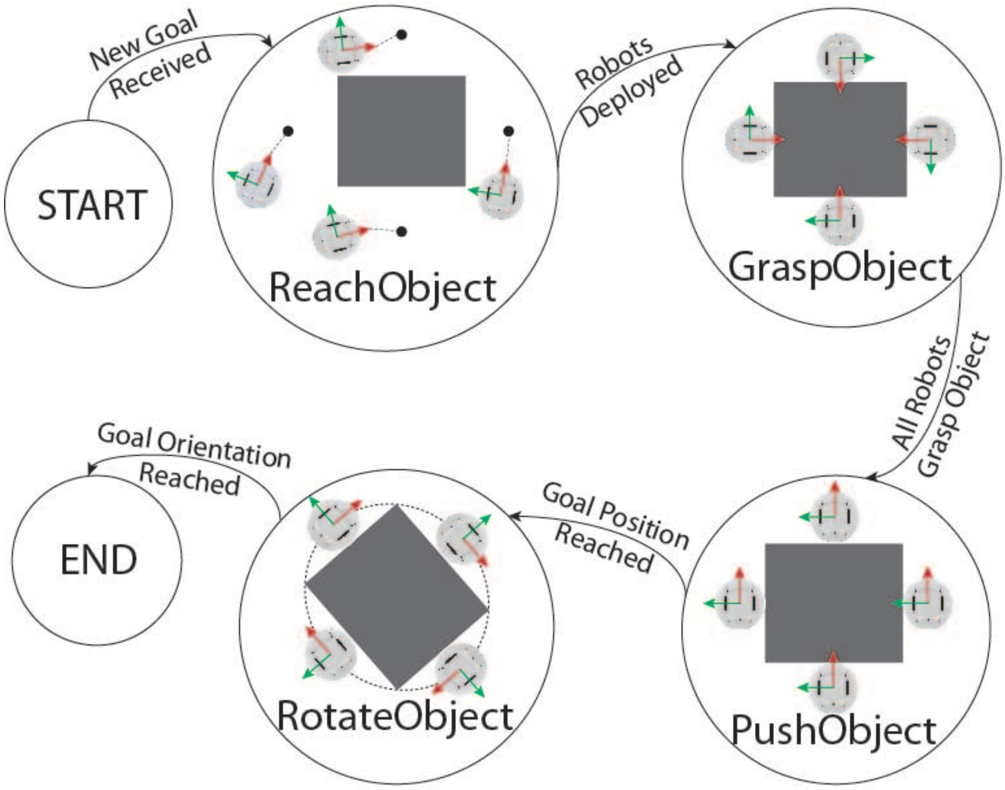
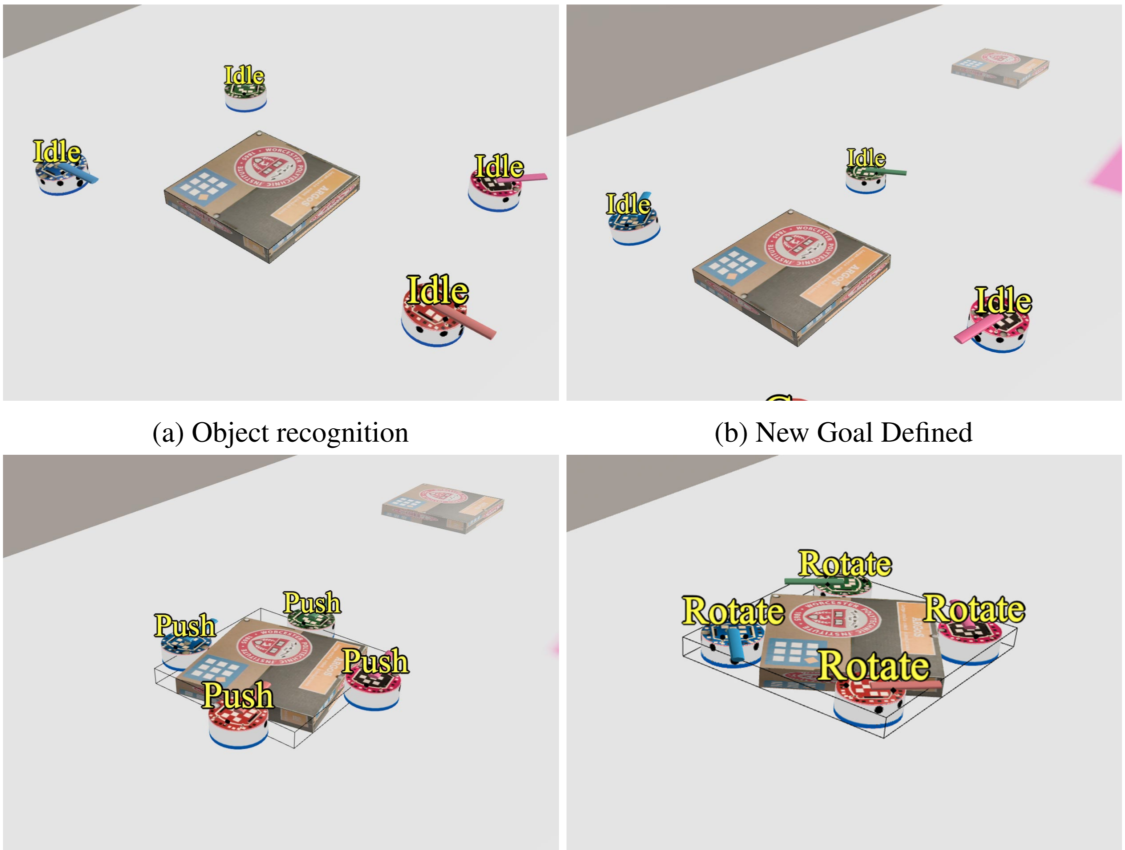


Figure 7.3: Collective transport state machine.

team pause their operation until the selected robot reaches the desired position. In case the robot is a part of an operator-defined team, the selected robot navigates to the newly specified position and other robots continue their respective operations. When two or more operators want to manipulate the same robot, the interface processes the position specified by the last operator. Fig. 7.5a shows a selected robot overlaid with a bounding box to visualize the current selection. Fig. 7.5b shows the goal position determined by the operator and visualized as a colored representation of the selected robot. The color of the goal position matches the color of the fiducial markers to differentiate between the goal positions of different robots. Fig. 7.5c shows the selected robot navigating to the specified goal position.

Robot Team Selection and Manipulation. In addition to manipulating a single robot, the operator can select a team of robots by pressing control key and clicking the left mouse



(a) Object recognition (b) New Goal Defined

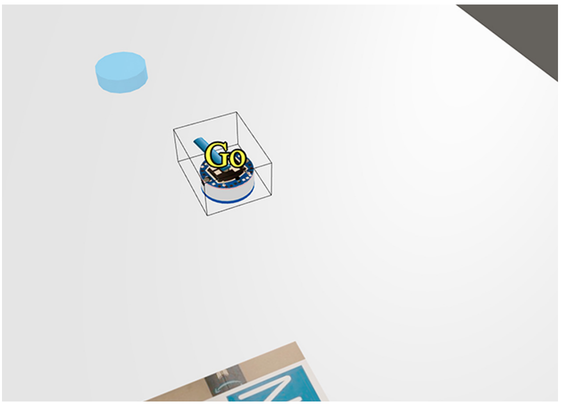
(c) Robots push the object (d) Robots rotate the object

Figure 7.4: Object manipulation by interaction with the object through the interface.

button. The goal position is still assigned with a right click. The interface overlays a transparent bounding box over all the selected robots to identify the current selection. If two or more operators have the same robot in their team, then the common robot navigates to the position specified by the last operator without affecting other robots in other teams. Fig. 7.6a shows a screenshot in which the selected robots are overlaid with a bounding box. Fig. 7.6b shows the goal position visualized as colored virtual objects, one for each of the selected robots. The color of the virtual objects matches the color of the fiducial markers on the body of the robots. Fig. 7.6c shows the robots navigating to the goal position.

(a) Robot selection

(b) New robot position

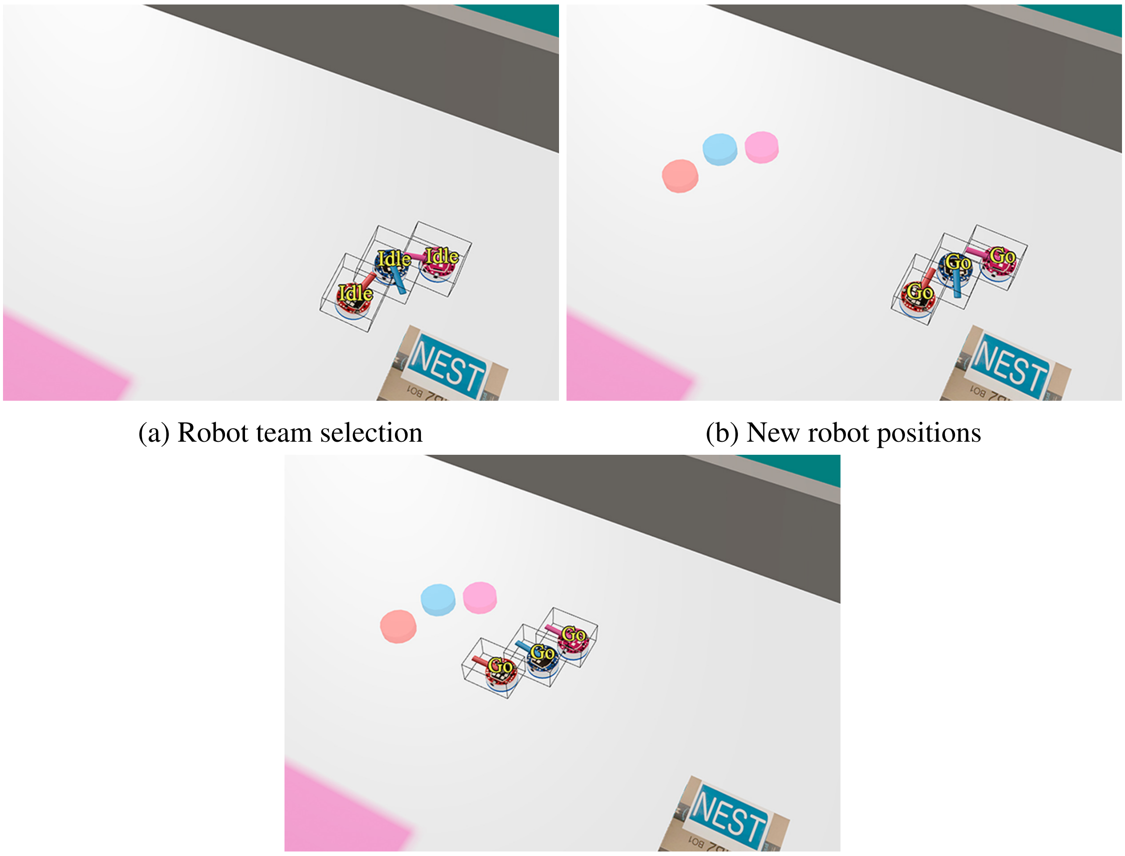


(c) Robot navigating to new position

Figure 7.5: Robot manipulation by interacting with the robots through the interface.

7.2.3 Transparency Modes

To investigate the role of various elements of the user interface, I endowed the client with the possibility to provide information to the user in several modalities. The main insight in my work is to consider the natural field of view of the human eye (see Fig. 7.7). I implemented the client to allow for both *central transparency*, i.e., displaying elements in the center of the screen or directly above robots and objects (green region in Fig. 7.7); and *peripheral transparency*, i.e., relegating interface elements to the borders of the screen (yellow region in Fig. 7.7). The key difference between central and peripheral transparency is the type and quantity of information displayed. With central transparency, the information is contextual and limited to the robots effectively visible on the screen



(a) Robot team selection

(b) New robot positions

(c) Robots navigating to new position

Figure 7.6: Robot team creation and manipulation by interacting with the interface.

(which changes as the operator modifies the camera pose). Peripheral transparency, on the other hand, always displays summary information on all the robots and the progress of each task.

The interface can be configured to show or hide every element. For the purposes of my work, I identified four essential "transparency modes":

- **No Transparency (NT).** The interface hides all the information originated by the robots or other operators. The operator can still interact with robots and objects using all the control modalities.

- **Central Transparency (CT).** The interface overlays a direction pointer and text

Figure 7.7: Central and peripheral regions of the field of view. The overlaid green region indicates the central field of view. The overlaid yellow region indicates the peripheral field of view.

to indicate the heading and current task of each robot (as shown in Fig. 7.8). The color of the pointer resembles the color of the fiducial markers on each robot to differentiate between multiple pointers. The robot status displays the current operation executed by the robot corresponding to the states of the collective transport finite state machine (see Fig. 7.3). Additionally, the interface indicates the commands of other operators, to foster shared awareness across operators. This information is available only for entities in the operator's field-of-view. The operator can move around in the environment to view information of other robots and objects that are not in the current field-of-view.

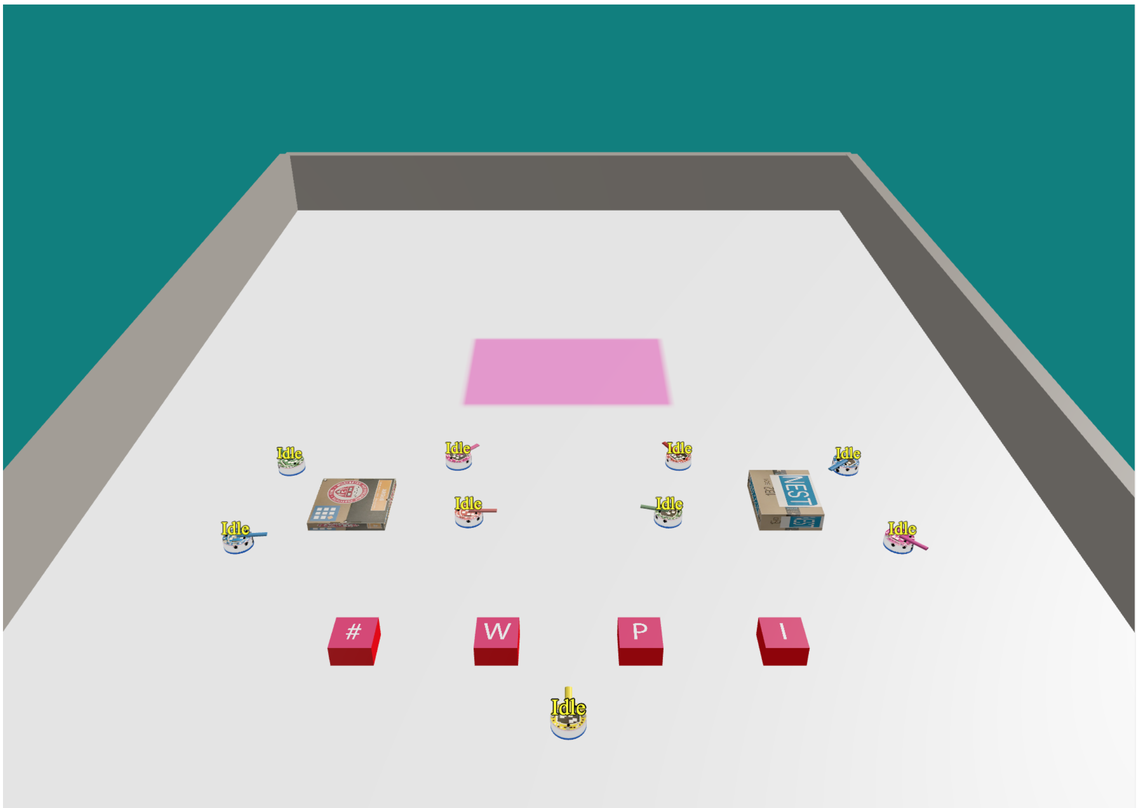


Figure 7.8: Central transparency showing on-robot status and directional indicator.

- **Peripheral Transparency (PT).** The interface offers a robot panel, an object panel, and a log window containing global information on the system and its constituents (see Fig. 7.9). The robot panel contains one icon for each robot. The panel highlights the icon corresponding to the robots that are moving or performing operator-defined actions. The panel also displays a warning, through a blinking exclamation point, to notify the operators of any fault conditions. These include getting stuck due to an obstacle, and software or hardware failures. The object panel shows all the objects in the environment. The interface highlights the objects currently manipulated by the robots. The panel also provides a functionality to select an object by clicking on the lock icon. An operator can convey their intention of manipulating an object by selecting the lock in the object panel. The interface highlights the lock with a blue icon to signify own selection and a red icon to indicate the selection of another

Figure 7.9: Peripheral transparency mode showing robot panel, object panel and a log (left to right).

operator. An operator can lock only one object at a time and cannot overwrite the selection of other operators.

- **Mixed Transparency (MT).** The interface also allows one to enable both central and peripheral transparency. In this case, the displayed information is a combination of the two transparency modes.

7.2.4 Communication Modes

Analogously to transparency modes, the interface also defines different modes for inter-human communication. I classify inter-human communication into direct, indirect, and a combination of both. The communication modes are described as follows.

- **No Communication (NC).** In this mode, the operators are completely unable to communicate with each other. The interface hides all the information originating from other operators, such as which robots are being used and which objects are being manipulated.

- **Direct Communication (DC).** In this mode, the operators can communicate verbally while performing the task. I established a verbal communication channel using Zoom[5], a video-conferencing application. The operators are allowed to ask for help and strategize at will towards the completion of the task.

- **Indirect Communication (IC).** In contrast to direct communication, in this mode the operators cannot verbally communicate their intentions and actions, but they can use the presented transparency modes to communicate indirectly. In this chapter, the choice of which transparency mode is active was determined by us at experiment time for the purposes of my study. In a realistic setting, however, each operator is allowed to choose the most appropriate mode.

- **Mixed Communication (MC).** In this mode, the operators can communicate both directly and indirectly throughout the duration of the experiment.

7.3 User Study under Ideal Conditions

7.3.1 Preliminaries

The main purpose of this first set of experiments is to validate the usability of the various transparency (T) and communication (C) modes under ideal conditions in remote interaction (R), i.e., with negligible loss of information. I base the experiments on the following main hypotheses.

[5] www.zoom.us

Hypotheses on the impact of different transparency modes:

- $\mathbf{H}_T^R\mathbf{1}$**:** Mixed transparency (MT) has the best outcome with respect to other modes.
- $\mathbf{H}_T^R\mathbf{2}$**:** Operators prefer mixed transparency (MT) over other modes.
- $\mathbf{H}_T^R\mathbf{3}$**:** Operators prefer central transparency (CT) over peripheral transparency (PT).

Hypotheses on the impact of different communication modes:

- $\mathbf{H}_C^R\mathbf{1}$**:** Mixed communication (MC) has the best outcome with respect to other modes.
- $\mathbf{H}_C^R\mathbf{2}$**:** Operators prefer mixed communication (MC) over other modes.
- $\mathbf{H}_C^R\mathbf{3}$**:** Operators prefer direct communication (DC) over indirect communication (IC).

Experimental Setup. I designed a game scenario (shown in Fig. 7.10) where the operators were given 9 robots to transport 6 objects (2 big and 4 small) to a goal region. Big objects were worth 2 points each, and small objects were worth 1 point each. The operators had to work as a team to score as many points as possible, over a maximum of 8, in experiments lasting 8 minutes. The operators could move the big objects using the collective transport behavior, or directly use individual robots or team manipulation commands to push the objects.

Participant Sample. For this user study, I recruited 28 university students. 14 of them (5 female, 9 male), with ages ranging from 19 to 37 years old (23.28 ± 4.38), performed the task four times with a different transparency mode (NT, CT, PT and MT) each time. The other 14 participants (4 female, 10 male), with ages ranging from 18 to 48 years old (23.64 ± 7.87), performed the task four times with a different communication mode (NC, DC, IC and MC) each time. I chosen the teams and the assignments at random. No participant had prior experience with the remote interface.

Figure 7.10: Remote study experiment setup.

Procedures. Each session of the study had two participants and approximately took a total of 105 minutes. After signing the consent form, I explained the task and gave each participant 10 minutes to familiarize with the system. I randomized the order of the tasks and the modalities to reduce the influence of learning effects. After each task, the participants had to answer a subjective questionnaire.

Metrics. I recorded subjective and objective measures for each participant and each task. I used the following common measures:

- **Situational Awareness.** I used the Situational Awareness Rating Technique (SART) [218] on a 4-point Likert scale [143] to assess the awareness of the situation after each task.

- **Task Workload.** I used the NASA TLX [90] scale on a 4-point Likert scale to

- Did you understand your *teammate's intentions*? Were you able to understand why your teammate was taking a certain action?
- Could you understand your *teammate's actions*? Could you understand what your teammate was doing at any particular time?
- Could you follow the *progress of the task*? While performing the tasks, were you able to gauge how much of it was pending?
- Did you understand what the *robots were doing*? At all times, were you sure how and why the robots were behaving the way they did?
- Was the information provided by the interface *clear to understand*?

Figure 7.11: The subjective questionnaire employed in the user study to assess the quality of interaction of an operator with the interface.

compare the perceived workload in each task.

- **Trust.** I used the trust questionnaire [224] on a 4-point Likert scale to compare the trust in the interface affected by each transparency mode.
- **Quality of Interaction.** I used a custom questionnaire on a 5-point Likert scale to assess the team-level and robot-level interaction. The interaction questionnaire is reported in Fig. 7.11.
- **Performance.** I used the points earned for each task as a metric to scale the performance achieved for each transparency mode.
- **Usability.** I asked participants to select the features (log, robot panel, object panel, and on-robot status) they used during the study. Additionally, I asked them to rank the transparency modes from 1 to 4, 1 being the highest rank.

Table 7.1: Results with relationships between transparency modes. The relationships are based on mean ranks obtained through a Friedman Test. The symbol * denotes significant difference ($p < 0.05$) and the symbol ** denotes marginally significant difference ($p < 0.10$). The symbol $^-$ denotes negative scales where lower ranking is better.

Attributes	Relationship	$\chi^2(3)$	p-value
SART SUBJECTIVE SCALE			
Instability of Situation$^-$	NT>PT>CT>MT**	9.554	0.023
Complexity of Situation$^-$	NT>PT>CT>MT**	16.950	0.001
Variability of Situation$^-$	not significant	2.452	0.484
Arousal	MT>CT>PT>NT**	8.550	0.036
Concentration of Attention	MT>CT>PT>NT**	11.898	0.008
Spare Mental Capacity	not significant	2.209	0.530
Information Quantity	MT>CT>PT>NT**	12.288	0.006
Information Quality	MT>CT>PT>NT**	28.758	< 0.001
Familiarity with Situation	CT>MT>PT>NT*	6.276	0.099
NASA TLX SUBJECTIVE SCALE			
Mental Demand$^-$	NT>PT>CT=MT**	10.800	0.013
Physical Demand$^-$	not significant	5.634	0.131
Temporal Demand$^-$	not significant	1.760	0.624
Performance	not significant	6.169	0.104
Effort$^-$	PT>NT>MT>CT**	6.630	0.085
Frustration$^-$	not significant	0.667	0.881
TRUST SUBJECTIVE SCALE			
Competence	MT>CT>PT>NT**	10.663	0.014
Predictability	MT>CT>PT>NT**	19.469	< 0.001
Reliability	MT>CT>PT>NT*	7.478	0.058
Faith	MT>CT>PT>NT**	15.138	0.002
Overall Trust	MT>CT>PT>NT**	18.210	< 0.001
Accuracy	MT>CT>PT>NT**	10.590	0.014
INTERACTION SUBJECTIVE SCALE			
Teammate's Intent	MT>CT>PT>NT**	9.923	0.019
Teammate's Action	MT>CT>NT>PT**	8.040	0.045
Task Progress	MT>CT>PT>NT*	6.532	0.088
Robot Status	MT>CT>PT>NT**	15.593	0.001
Information Clarity	CT>MT>PT>NT**	8.414	0.038
PERFORMANCE OBJECTIVE SCALE			
Points Scored	not significant	3.444	0.328

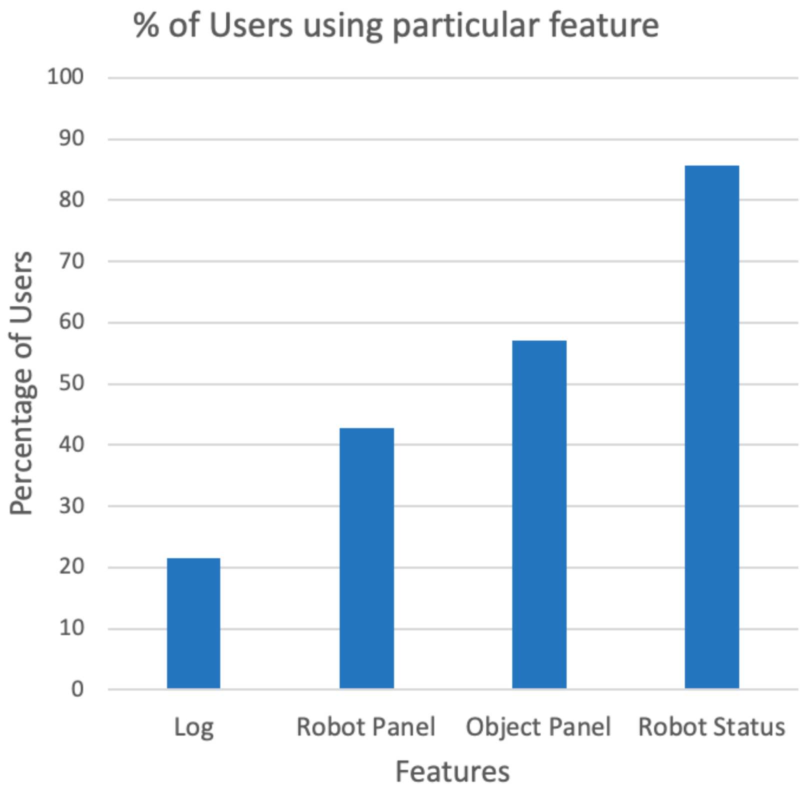


Figure 7.12: Feature usability in the transparency user study.

Table 7.2: Ranking scores, in the transparency user study, based on the Borda count. The gray cells indicate the leading scenario for each type of ranking.

Borda Count	NT	CT	PT	MT
Based on Collected Data Ranking (Table 7.1)	22	63.5	38	76.5
Based on Preference Data Ranking (Fig. 7.13)	16	40	29	55

7.3.2 Analysis and Discussion

Collected Data

Transparency Data. Table 7.1 shows the summarized results for all the subjective scales and the objective performance. I used the Friedman test [75] to analyze the data and assess the significance between different modes of transparency. I derived a ranking based on the mean ranks for all the attributes that showed statistical significance ($p < 0.05$) or marginal

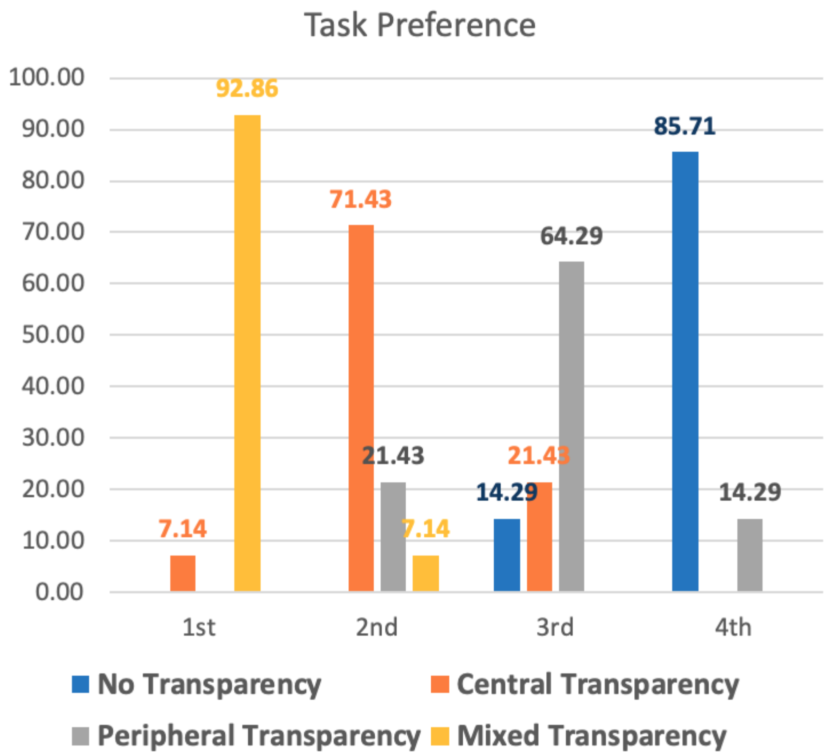


Figure 7.13: Task preference in the transparency user study.

significance ($p < 0.10$). Fig. 7.12 shows the percentage of operators using a particular feature. Fig. 7.13 shows the percentage of people ranking a task based on their choice. I used the Borda count [20] method for calculating the overall ranking of the collected data and transparency mode usability data. I inverted the ranking of the negative scales for calculating the Borda count scores. Table 7.2 shows the results of the Borda count for each category.

Communication Data. Table 7.3 shows the summarized results of the communication user study. I analyzed the data using the Friedman test [75] to assess the significant relationships among different modes of communication. I used statistical significance ($p < 0.05$) and marginal significance ($p < 0.10$) to derive a ranking based on their mean ranks. Fig. 7.14 shows the percentage of operators using a particular feature. Fig. 7.15 shows the percentage of people ranking task based on their choice. Using the Borda count

Table 7.3: Results with relationships between communication modes. The relationship are based on mean ranks obtained through Friedman Test. The symbol * denotes significant difference ($p < 0.05$) and the symbol ** denotes marginally significant difference ($p < 0.10$). The symbol $^-$ denotes negative scales and lower ranking is a good ranking.

Attributes	**Relationship**	$\chi^2(3)$	p**-value**
SART SUBJECTIVE SCALE			
Instability of Situation$^-$	NC>DC>IC>MC**	29.105	< 0.001
Complexity of Situation$^-$	NC>IC>DC>MC**	14.921	0.002
Variability of Situation$^-$	NC>DC>IC>MC**	9.280	0.026
Arousal	MC>DC>IC>NC**	28.240	< 0.001
Concentration of Attention	MC>DC>IC>NC**	24.570	< 0.001
Spare Mental Capacity	MC>DC>IC>NC**	23.579	< 0.001
Information Quantity	not significant	3.286	0.350
Information Quality	not significant	4.168	0.244
Familiarity with Situation	MC>DC>IC>NC**	12.282	0.006
NASA TLX SUBJECTIVE SCALE			
Mental Demand$^-$	NC>IC>DC>MC**	21.023	< 0.001
Physical Demand$^-$	NC>IC>DC>MC**	14.870	0.002
Temporal Demand$^-$	NC>IC>DC>MC**	17.433	0.001
Performance	MC>DC>IC>NC**	12.429	0.006
Effort$^-$	NC>IC>DC>MC**	25.093	< 0.001
Frustration$^-$	NC>IC>DC>MC**	9.961	0.019
TRUST SUBJECTIVE SCALE			
Competence	MC>DC>IC>NC**	23.195	< 0.001
Predictability	MC>IC>DC>NC**	16.059	0.001
Reliability	MC>IC>DC>NC*	6.861	0.076
Faith	MC>DC>IC>NC**	13.425	0.004
Overall Trust	MC>DC>IC>NC**	17.396	0.001
Accuracy	MC>DC>IC>NC**	16.171	0.001
INTERACTION SUBJECTIVE SCALE			
Teammate's Intent	MC>DC>IC>NC**	19.848	< 0.001
Teammate's Action	MC>DC>IC>NC**	21.258	< 0.001
Task Progress	MC>DC>IC>NC**	13.176	0.004
Robot Status	MC>IC>DC>NC**	13.991	0.003
Information Clarity	MC>IC>DC>NC**	25.160	< 0.001
PERFORMANCE OBJECTIVE SCALE			
Points Scored	not significant	3.444	0.328

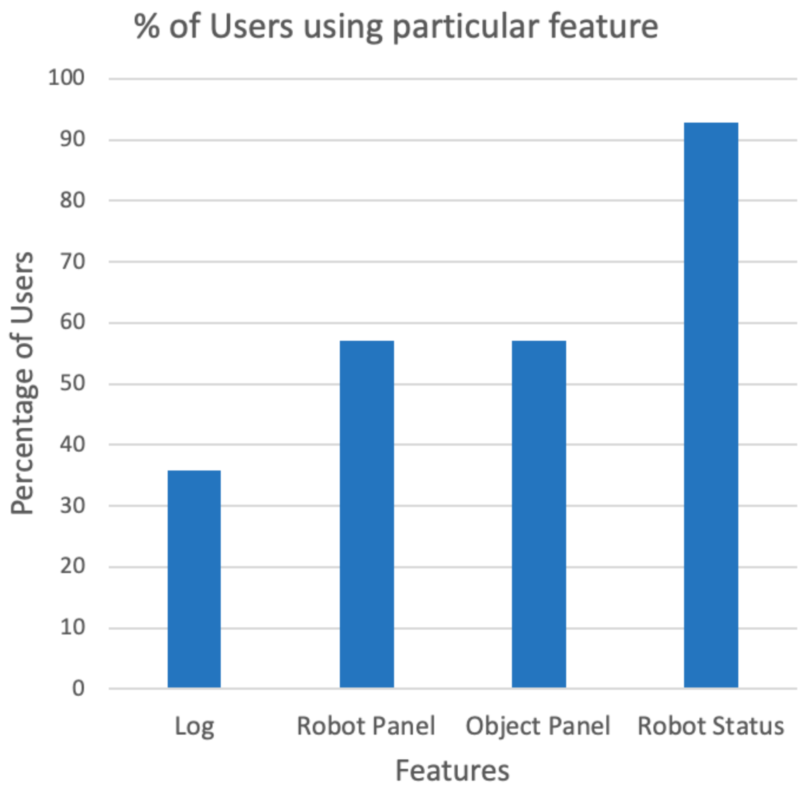


Figure 7.14: Feature usability in the communication user study.

Table 7.4: Ranking scores, in the communication user study, based on the Borda count. The gray cells indicate the leading scenario for each type of ranking.

Borda Count	NC	DC	IC	MC
Based on Collected Data Ranking (Table 7.3)	24	67	53	96
Based on Preference Data Ranking (Fig. 7.15)	16	38	30	56

method, I derived an overall ranking based on the collected data and the user preference data (shown in Table 7.4).I inverted the ranking of the negative scales for the Borda count scores.

Transparency Modes

Table 7.2 shows that mixed transparency (MT) is the best transparency mode in terms of usability, supporting hypotheses $\mathbf{H}_T^R\mathbf{1}$ and $\mathbf{H}_T^R\mathbf{2}$. From the results, central transparency

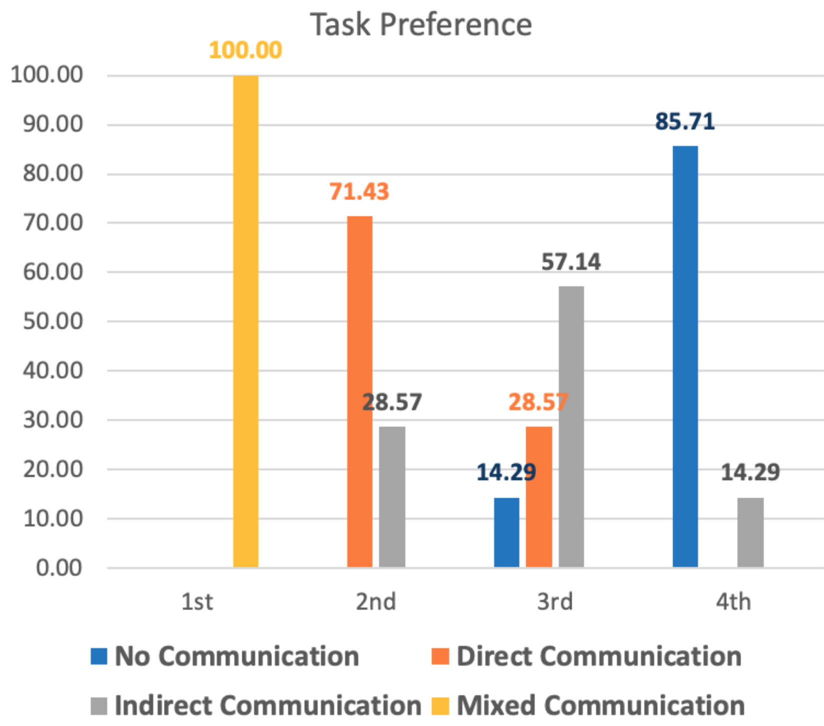


Figure 7.15: Task preference in the communication user study.

(CT) dominates peripheral transparency (PT), supporting hypothesis $\mathbf{H}^{R}_{T}\mathbf{3}$. In addition to this, I also analyzed the modes of transparency based on the sub-scales of the subjective data and further analysed for each mode as follows.

Mixed Transparency. This mode is the overall best choice for the operators. The results suggest that this mode provides the operators with the best situational awareness, measured in terms of least instability of situation, complexity of situation, best information arousal, level of concentration, information quality, and information quantity. Through this transparency mode, the operators had the most information about actions and intentions of teammates and robots, as well as of the task progress. This led the operators to report the highest trust across all trust sub-scales.

Central Transparency. This mode is the second best choice after mixed transparency. The operators had the best familiarity and clarity in terms of information provided by the interface. The operators experienced the lowest mental load and reported the least effort in performing the task. Fig. 7.12 supports these findings as 92% (13 out of 14 operators) indicated the on-robot status as the most useful feature.

Peripheral Transparency. The operators reported peripheral transparency as the most cumbersome mode. The operators experienced the lowest awareness, which caused degraded trust. The operators reported that the mode was merely better than no transparency (NT), because the presence of *some* information is still better than *no* information.

Comparison with Proximal Interaction. Overall, the conclusions of this study are in line those I reported for proximal interaction (see Chapter 5). However, the results in this chapter are more substantial compared to what I observed for proximal interaction. Unlike proximal interaction, mixed transparency in remote interaction was the clear winner, both from the collected data ranking and the preference data ranking (see Table. 7.2). Central transparency not only outperformed peripheral transparency in remote interaction, but dominated the results when compared to the findings of the study with proximal interaction. I speculate that this difference is due to the fact that, in proximal interaction, the operators had to devote effort to avoid bumping into robots and other operators while walking. This made the operators alert and anxious, affecting their focus on the information offered by the interface and the transparency modes. In remote interaction, as there was no need to physically move, the operators could focus on the displayed information more effectively.

Our experiments did not reveal a substantial difference in performance across transparency modes. I hypothesize that this lack of difference is due to the learning effect across the four runs that each team had to perform. Fig. 7.16 shows the performance in each task and Fig. 7.17 reports the increase in performance due to the task order (learning effect). As most of the teams were able to complete the task in less than 8 minutes, Fig. 7.18 shows the decrease in time taken to complete the task in order of the performed task, indicating the impact of the learning effect.

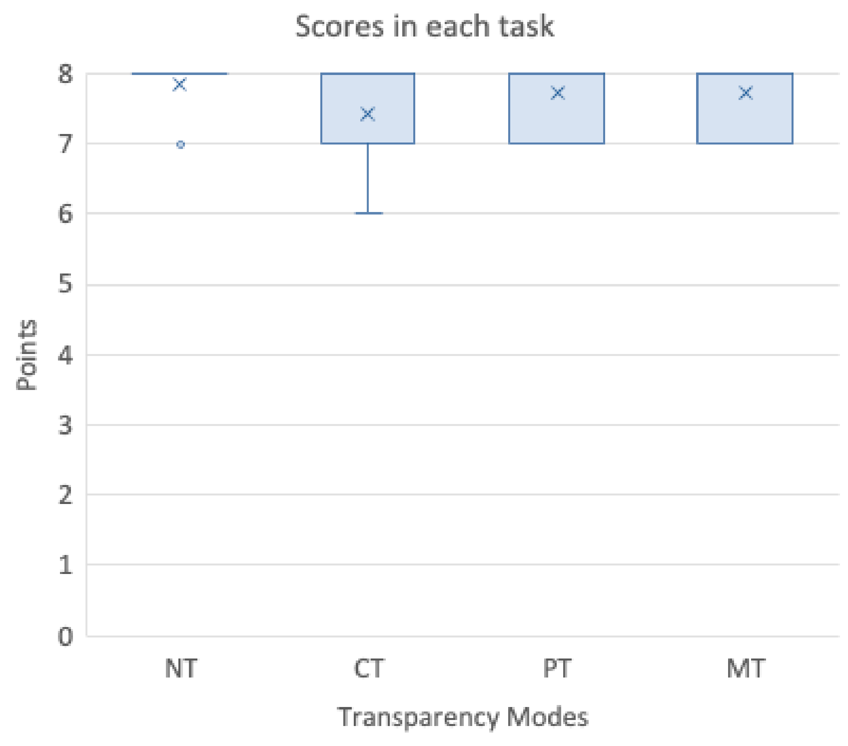


Figure 7.16: Task performance for each transparency mode.

Modes of Communication

Table 7.4 suggests that mixed communication (MC) is the best mode of communication, both in terms of usability preference and in terms of the data collected during the user study, supporting hypotheses $\mathbf{H}_C^R\mathbf{1}$ and $\mathbf{H}_C^R\mathbf{2}$. In addition, direct communication (DC) outperformed indirect communication (IC), confirming hypothesis $\mathbf{H}_C^R\mathbf{3}$. I also analysed the modes of communication based on the sub-scales of the subjective data and further analysed for each mode.

Mixed Communication. Mixed communication was recognized as the best mode, not only based on the Borda count but also looking at the results of the subjective data. This mode had the best situational awareness, trust in the system, and interaction with the robots and the operator, while having the lowest task load.

Direct Communication. This mode was the second best. It outperformed indirect

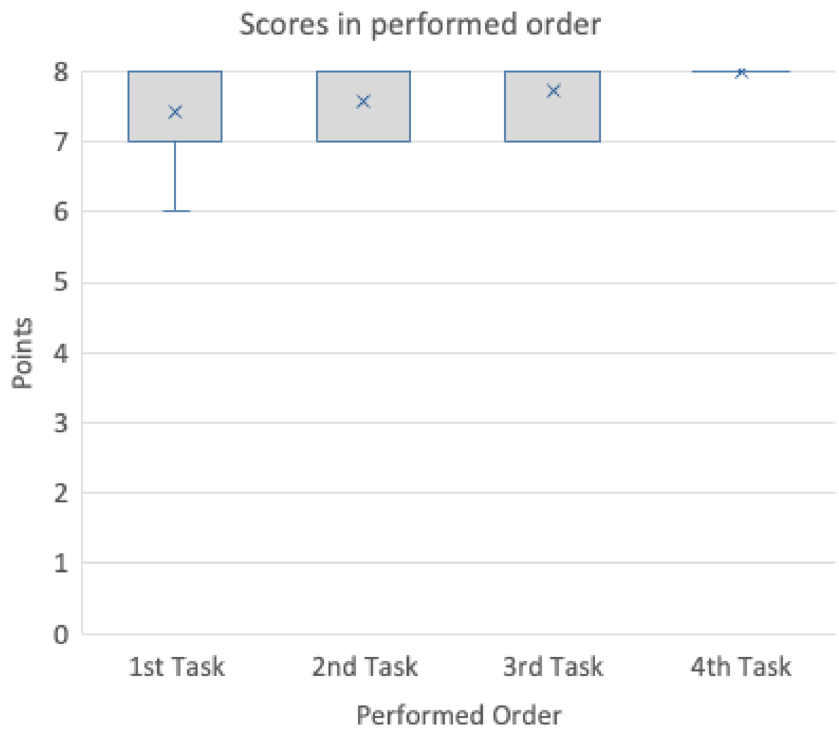


Figure 7.17: Learning effect in the transparency user study based on points scored.

communication in terms of information awareness and communication with the other operator (operator-level information), resulting in better trust in the system and lower workload with respect to indirect communication.

Indirect Communication. This mode was the third best choice. This mode proved to be better in conveying robot-level information, thus allowing the operator to better understand and predict robot actions, when compared to direct communication. This made the operators trust this mode more in terms of predictability and reliability, but at the cost of experiencing higher workload in comparison to mixed communication and direct communication.

Comparison with Proximal Interaction. Analogously to what I said about transparency, these observations are in line with the results of the proximal interaction study. However, the results of this study were more decisive with respect to the proximal interac-

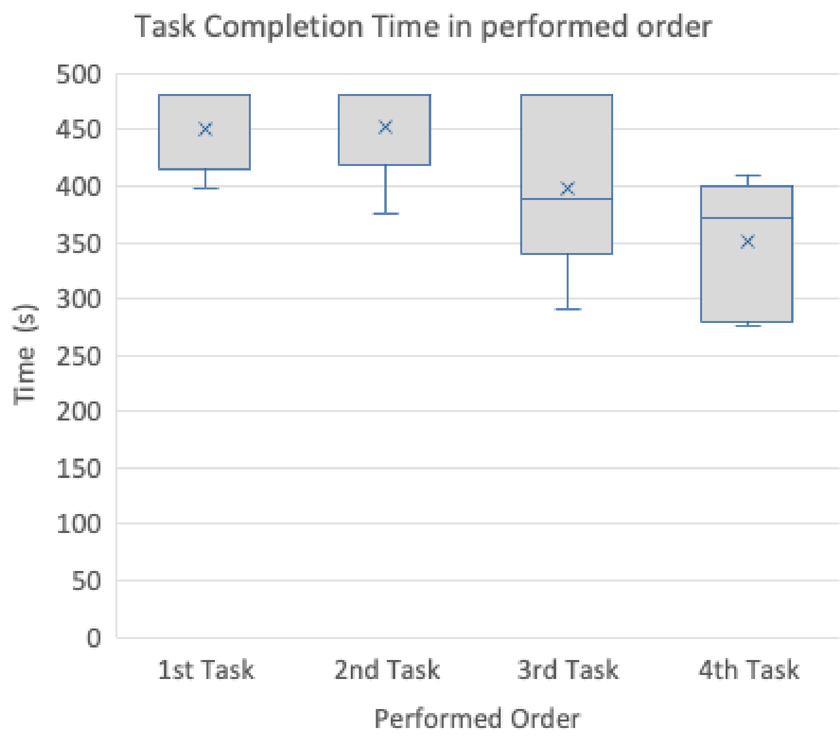


Figure 7.18: Learning effect in the transparency user study based on time taken to complete the task.

tion study. Also in this case, I observed that the proximal interaction made the operators alert and anxious about robots and the other operator. Also, as the operators had to physically walk around other robots, the interaction felt at times cumbersome. This observation is supported by workload results of the proximal interaction studies in Chapter 6, indicating high workload experienced in all modes of communication. In contrast, the results of workload in remote interaction showed significant difference between communication modes.

Our experiments did not reveal a significant difference in performance across communication modes. Similarly to what I discussed for transparency, I hypothesize that this lack of difference is due to the learning effect across the four runs that each team had to perform. Fig. 7.19 indicates the points earned by the operators in each task and Fig. 7.20 shows the learning effect as the increase in points earned in order of the performed task. As

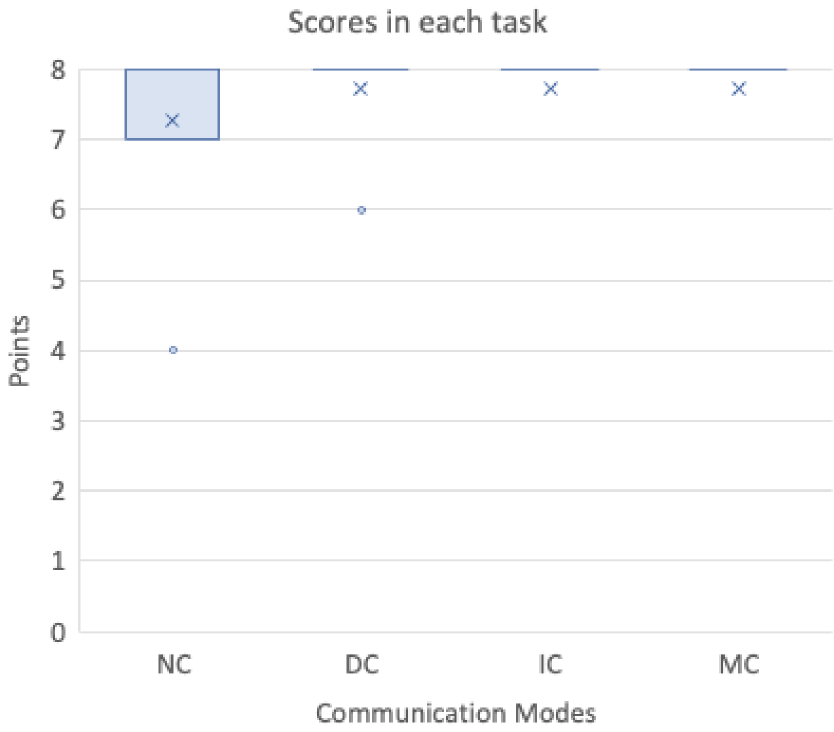


Figure 7.19: Task performance for each communication mode.

most of the operator teams were able to complete the task earlier than 8 minutes, Fig. 7.21 shows the decrease in time taken to complete the task in order of the performed task as a clear indicator of the learning effect.

7.4 User Study with Information Loss

The study presented so far was based on the assumption that the information flow was fast and continuous for every operator. This was possible because all the users involved in the experimental evaluation had fast, stable Internet connections that showed no issues. However, in remote operations, fast and stable connectivity cannot be taken for granted.

For this reason, I investigate the role that intermittent information flow plays in the efficiency of remote multi-human multi-robot interaction. In the rest of chapter, I measure information loss as the time elapsed between two updates of the graphical user interface.

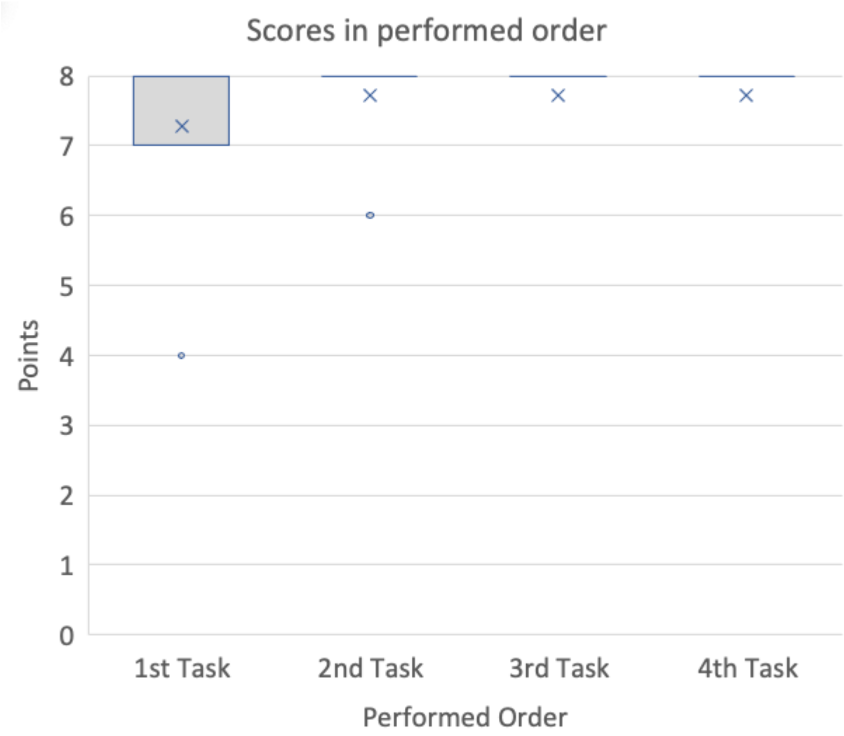


Figure 7.20: Learning effect in the communication user study.

In other words, I define information loss as the inverse of the frame rate. With operators and robots in separate environments, it is likely for the operators to experience different levels of information loss. When this happens, I speak of *heterogeneous* information loss.

For the purposes of the study, I categorize information loss in two ranges of usability. The *high usability range* (U_H) corresponds to levels of information loss that cause negligible discomfort in the operators that experience it. Conversely, we are in *low usability range* (U_L) when the level of information loss is such that an operator cannot ignore its presence, experiencing some sort of discomfort.

In general, the exact extent of these ranges changes with the operators. I thus split the study in two parts. In the *pilot study* (Sec. 7.4.1), I investigate the extent of the usability ranges in experiments that involve a single operator. Next, in the *main study* (see Sec. 7.4.2), I turn to multiple operators and assess the effect of heterogeneous information loss, using the homogeneous case as a baseline reference.

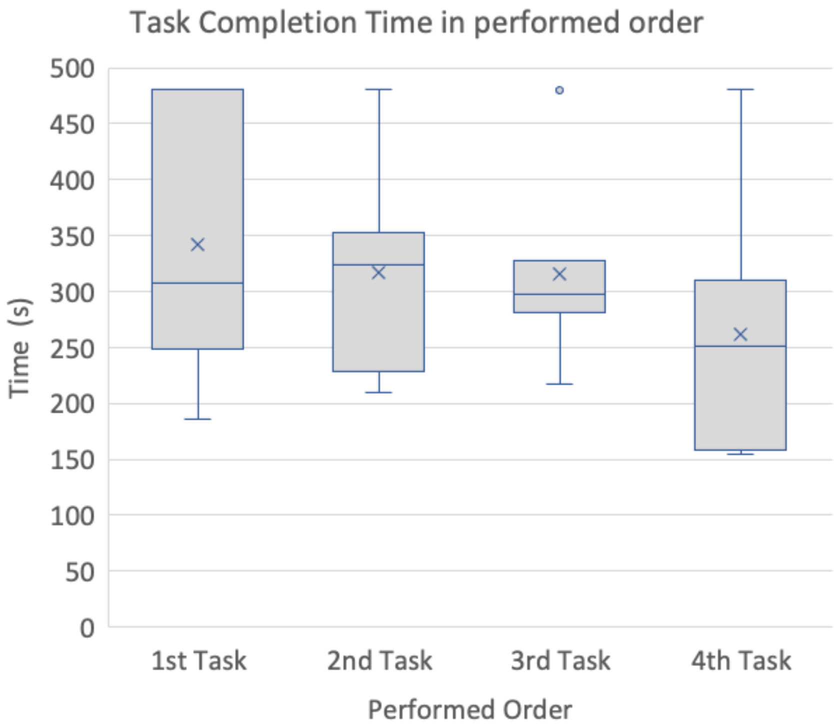


Figure 7.21: Learning effect in the communication user study.

7.4.1 Information Loss Pilot Study

Experimental Setup. For the pilot study with a single operator I used the game scenario presented in Sec. 7.3 (see Fig. 7.10). The operator was tasked with performing half of the game: moving 1 big object and 2 small objects. In contrast to the previous game, I set no time limit to complete the task, instead declaring completion when the required objects reached the goal region. Every participant had to perform the task 6 times with different levels of information loss each time. The levels spanned from 0 s to 2.5 s in increments of 0.5 s. To compensate for possible learning effects or other confusing factors, I determined different level orderings:

- **Increasing order**: information loss increases with every task.
- **Decreasing order**: the information loss decreases with every task.

- **Random 1**: information loss is in the order $\{0, 2.5, 0.5, 2, 1, 1.5\}$ s.

- **Random 2**: the reverse order with respect to Random 1.

Participant Sample. I recruited 20 university students (7 females, 13 males) with ages ranging from 18 to 31 years old (22.75 ± 3.57). All participants were randomly assigned one task ordering. Each participant performed the 6 tasks in the determined order. No participant had prior experience with the remote interface.

Pilot Study Procedure. Each session of the study took approximately 90 minutes. After signing the consent form, I explained the task setup and gave the participant 12 minutes to familiarize with the system. After each task, the participant had to answer a subjective questionnaire.

Metrics. I recorded the subjective and objective measures for each participant for each task. The performance of the operator was measured as time taken to complete a task. I used the NASA TLX [90] scale on a 10-point Likert scale to compare the perceived workload in each task. In addition to the workload questionnaire, the participants were requested to report the experienced discomfort on a 10-point Likert Scale, followed by a comment box for free-form description of the type of discomfort experienced.

Results. For each item in the NASA TLX scale, I report a significance matrix based on the Friedman test to identify the two ranges of usability. The results are shown in Tables 7.5-7.12. The green cells in these tables indicate the high usability range and the red cells indicate the low usability range. I also superimposed the usability ranges in Table 7.13. From the data, I estimate the high usability range between 0 s and 0.5 s, and the low usability range between 2 s and 2.5 s. For the upcoming main study on information loss (Sec. 7.4.2), I took the midpoints of these ranges (0.25 s and 2.25 s). Figures 7.22-7.29 report the box plots of the recorded readings for the respective metrics.

Table 7.5: Significance matrix for differences in performance between levels of information loss. The shaded regions indicate the two ranges of usability. The cell entries are the p-values based on the Friedman test. The empty cells represent a comparison with no significant difference.

Performance	**0s**	**0.5s**	**1s**	**1.5s**	**2s**	**2.5s**
0s			0.007	0.007	<0.001	0.002
0.5s					0.025	0.025
1s	0.007				0.025	0.025
1.5s	0.007					
2s	<0.001	0.025	0.025			
2.5s	0.002	0.025	0.025			

Table 7.6: Significance matrix for differences in mental load between levels of information loss. The shaded regions indicate the two ranges of usability. The cell entries are the p-values based on the Friedman test. The empty cells represent a comparison with no significant difference.

ML	**0s**	**0.5s**	**1s**	**1.5s**	**2s**	**2.5s**
0s			<0.001	0.008	<0.001	<0.001
0.5s			0.008		0.012	0.003
1s	<0.001	0.008				0.018
1.5s	0.008				0.033	0.005
2s	<0.001	0.012		0.033		0.002
2.5s	<0.001	0.003	0.018	0.005	0.002	

Table 7.7: Significance matrix for differences in physical load between levels of information loss. The shaded regions indicate the two ranges of usability. The cell entries are the p-values based on the Friedman test. The empty cells represent a comparison with no significant difference.

PL	**0s**	**0.5s**	**1s**	**1.5s**	**2s**	**2.5s**
0s		0.007	0.004	0.002	<0.001	<0.001
0.5s	0.007		0.008	0.004	0.02	0.033
1s	0.004	0.008				
1.5s	0.002	0.004				
2s	<0.001	0.02				
2.5s	<0.001	0.033				

Table 7.8: Significance matrix for differences in temporal load between levels of information loss. The shaded regions indicate the two ranges of usability. The cell entries are the p-values based on the Friedman test. The empty cells represent a comparison with no significant difference.

TL	**0s**	**0.5s**	**1s**	**1.5s**	**2s**	**2.5s**
0s				0.013		
0.5s				0.046		
1s						
1.5s	0.013	0.046				
2s						
2.5s						

Table 7.9: Significance matrix for differences in perceived performance between levels of information loss. The shaded regions indicate the two ranges of usability. The cell entries are the p-values based on the Friedman test. The empty cells represent a comparison with no significant difference.

PP	**0s**	**0.5s**	**1s**	**1.5s**	**2s**	**2.5s**
0s				0.021	0.002	
0.5s			0.034	0.02	0.033	0.033
1s		0.034				
1.5s	0.021	0.02				
2s	0.002	0.033				
2.5s		0.033				

Table 7.10: Significance matrix for differences in effort between levels of information loss. The shaded regions indicate the two ranges of usability. The cell entries are the p-values based on the Friedman test. The empty cells represent a comparison with no significant difference.

E	**0s**	**0.5s**	**1s**	**1.5s**	**2s**	**2.5s**
0s			0.005		0.018	0.039
0.5s			0.029		0.013	0.046
1s	0.005	0.029				
1.5s						
2s	0.018	0.013				
2.5s	0.039	0.046				

Table 7.11: Significance matrix for differences in frustration between levels of information loss. The shaded regions indicate the two ranges of usability. The cell entries are the p-values based on the Friedman test. The empty cells represent a comparison with no significant difference.

F	0s	0.5s	1s	1.5s	2s	2.5s
0s			0.012	0.002	<0.001	<0.001
0.5s	0.012		<0.001	0.02	<0.001	0.001
1s	0.002	<0.001				0.018
1.5s	0.001	0.02			0.029	0.005
2s	<0.001	<0.001		0.029		
2.5s	<0.001	0.001	0.018	0.005		

Table 7.12: Significance matrix for differences in visual discomfort between levels of information loss. The shaded regions indicate the two ranges of usability. The cell entries are the p-values based on the Friedman test. The empty cells represent a comparison with no significant difference.

VD	0s	0.5s	1s	1.5s	2s	2.5s
0s				0.035	0.001	0.013
0.5s					0.004	0.021
1s						
1.5s	0.035					
2s	0.001	0.004				
2.5s	0.013	0.021				

Table 7.13: Overlaid significance matrices for determining the range of operability.

VD	0s	0.5s	1s	1.5s	2s	2.5s
0s						
0.5s						
1s						
1.5s						
2s						
2.5s						

7.4.2 Information Loss Main Study

Experimental Setup. The final study I performed concerns the role of information loss in remote interaction between multiple humans and multiple robots. A particular aspect I

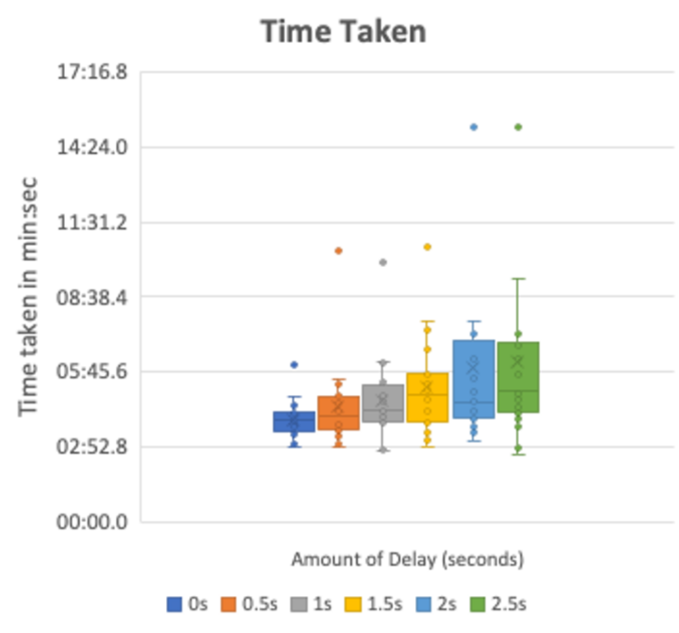


Figure 7.22: Box plot for performance, in time taken to complete the task. Lower is better.

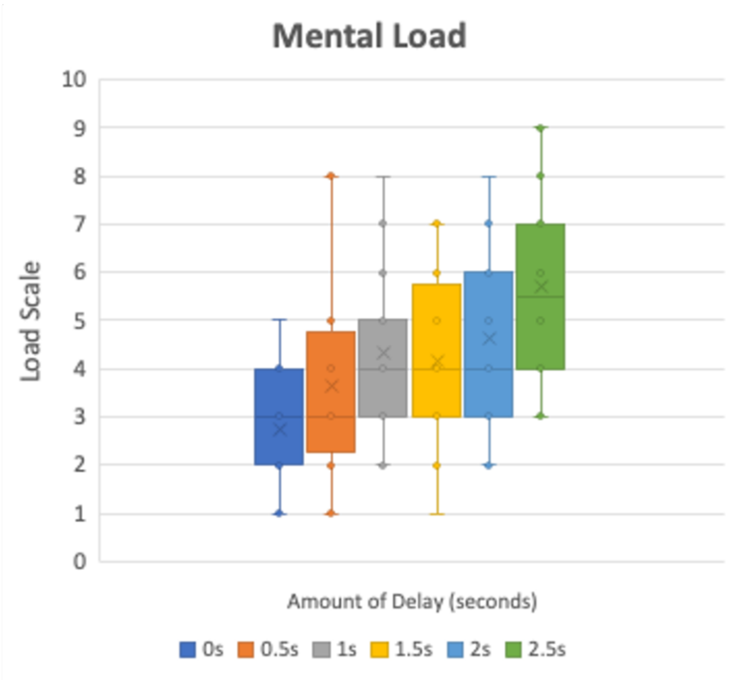


Figure 7.23: Box plot for reported mental load. Lower is better.

intend to explore is the role of heterogeneous information loss across operators. To this aim, I consider also the homogeneous case as a baseline. From the results of the pilot study

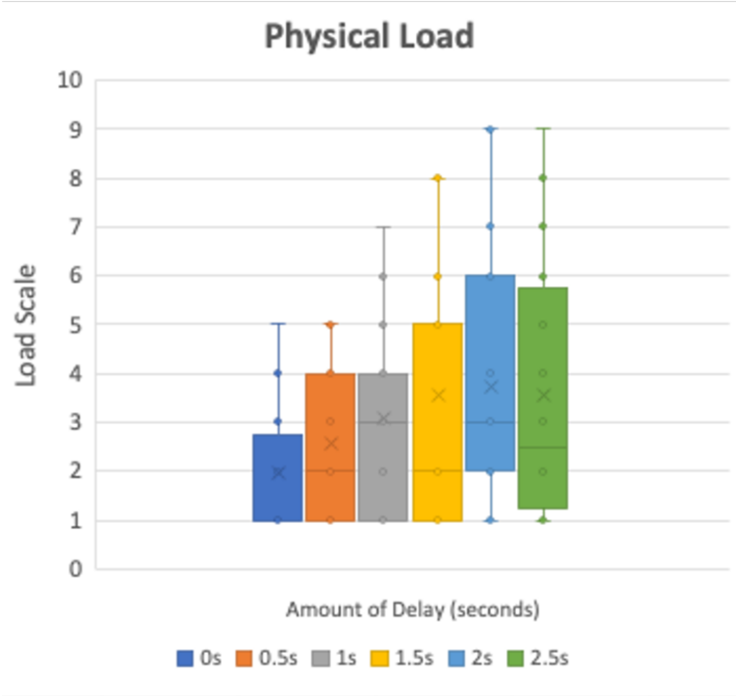


Figure 7.24: Box plot for reported physical load. Lower is better.

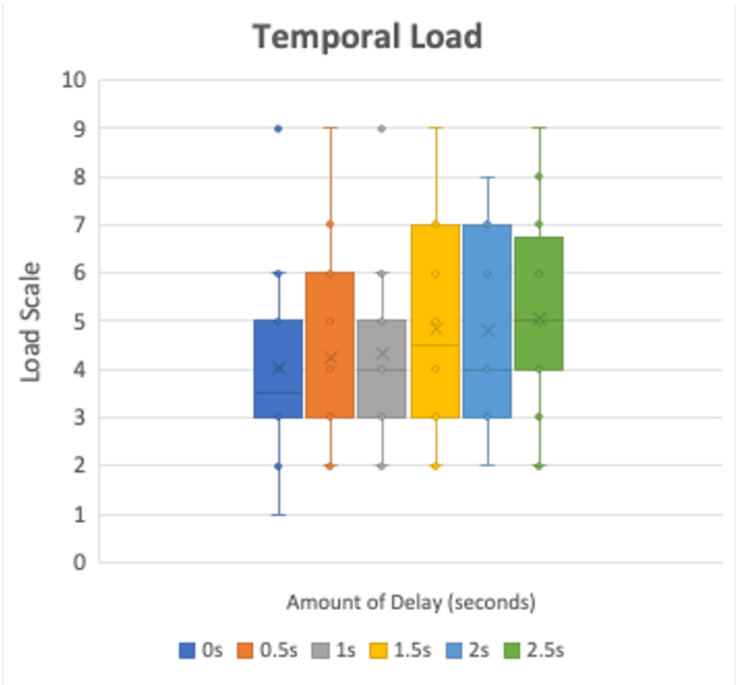


Figure 7.25: Box plot for reported temporal load. Lower is better.

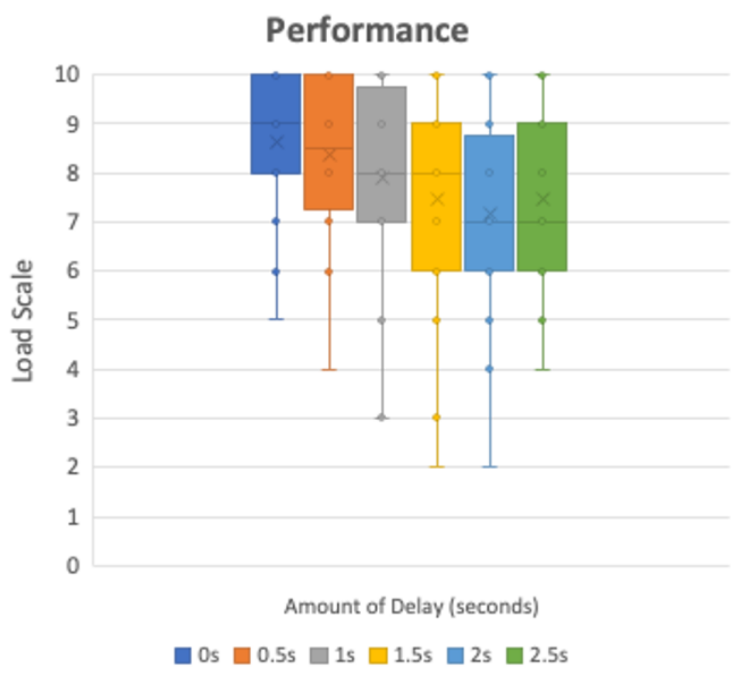


Figure 7.26: Box plot for reported perceived performance. Higher is better.

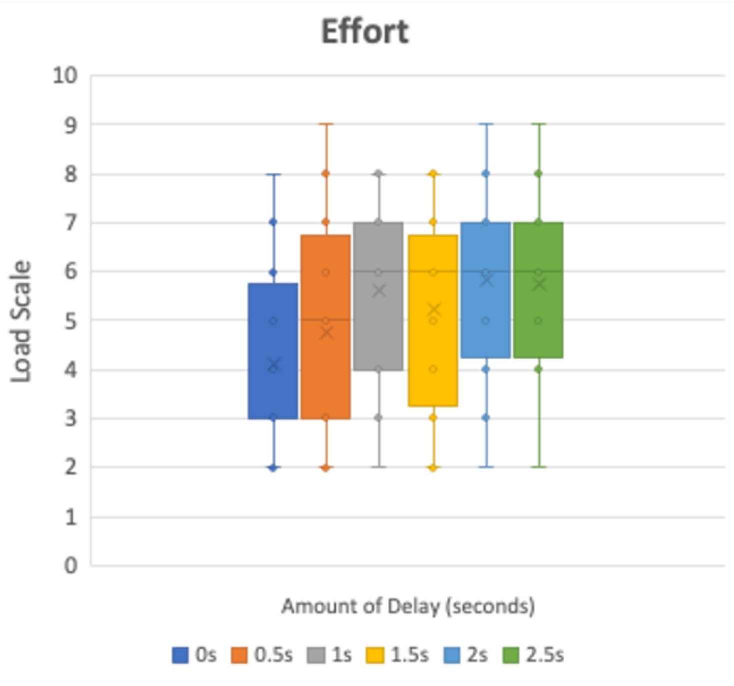


Figure 7.27: Box plot for reported effort. Lower is better.

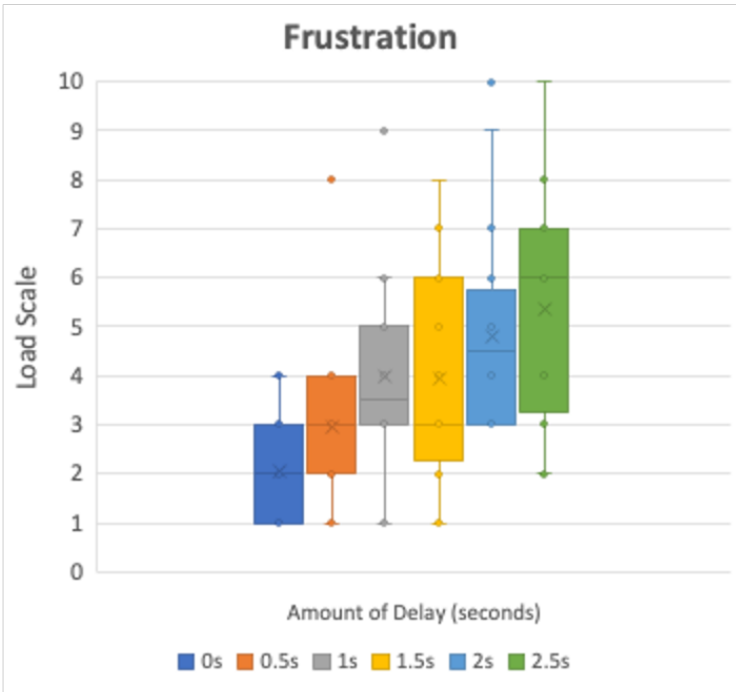


Figure 7.28: Box plot for reported frustration. Lower is better.

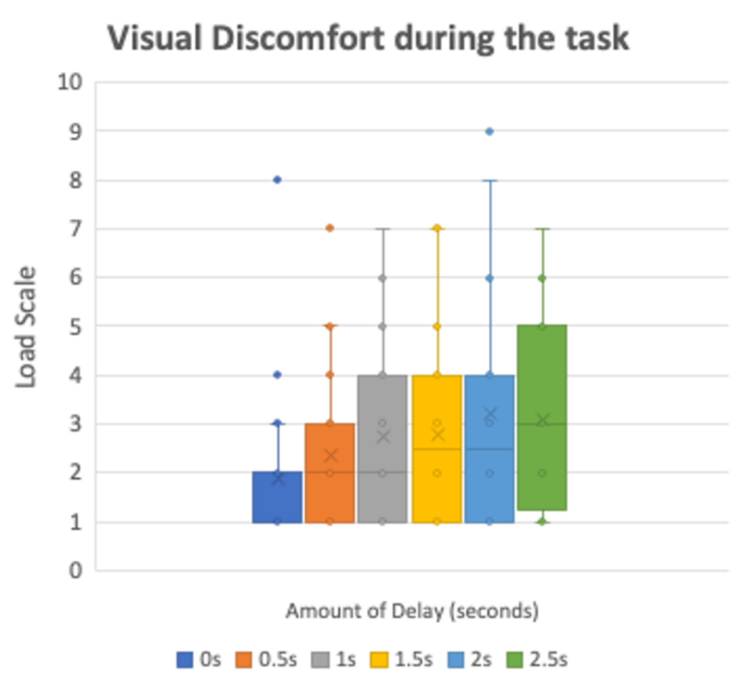


Figure 7.29: Box plot for reported visual discomfort. Lower is better.

in Sec. 7.4.1, I identified two levels of information loss: a low level, corresponding to high usability (0.25 s), and a high level, corresponding to low usability (2.25 s). I again used the collective transport game scenario and asked every participant to perform four experiments, one for each combination of levels of information loss for the operators. Once more, I randomized the order of the tasks to mitigate learning effects and other artifacts. In the following figures and tables, I use the following symbols to denote the four cases:

- Ho_{LL}: low homogeneous information loss;
- Ho_{HH}: high homogeneous information loss;
- He_{LH}: heterogeneous information loss in which operator 1 has low loss and operator 2 has high loss;
- He_{HL}: heterogeneous information loss in which the operators are reversed with respect to He_{LH}.

Hypotheses. I seek to validate the following working hypotheses:

- $\mathbf{H}_{IL}\mathbf{1}$: The case of low homogeneous information loss is the best overall with respect to the other cases in terms of measured metrics.
- $\mathbf{H}_{IL}\mathbf{2}$: The operators prefer low homogeneous information loss to the other cases.
- $\mathbf{H}_{IL}\mathbf{3}$: In the heterogeneous information loss case, operators prefer to be the ones with low information loss.
- $\mathbf{H}_{IL}\mathbf{4}$: Operators prefer to experience high information loss in the heterogeneous case to being in the high homogeneous loss case.

Participant Sample. I randomly paired the participants of the pilot study, forming 10 teams. Each team went through the four aforementioned cases.

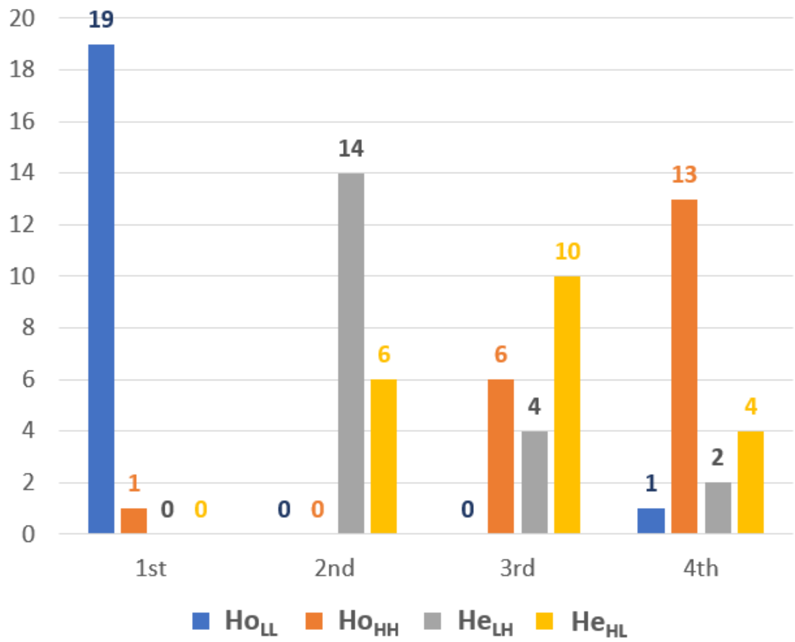


Figure 7.30: Operator preferences in information loss.

Procedures. Each session took approximately 105 minutes. Each session began with a training period, followed by 12 minutes of independent exploration of the system by the participants. After each session, each participant had to answer a subjective questionnaire.

Metrics. I recorded subjective objective metrics for each participant and for each case. I used the same metrics presented in Sec. 7.3. In addition, I recorded the number of interactions the participants made with the interface, as well as the time interval between those interactions. This allowed us to analyze the difference in workload between operators of the same team.

Results. Tables 7.14 and 7.15 show the summarized results for the subjective scales and the objective metrics. I used the Friedman test to establish significance between different cases. I formed rankings based on the mean ranks for all the attributes that showed statistical significance ($p < 0.05$) or marginal significance ($p < 0.10$). Tables 7.17 and 7.18 report an imbalance in awareness, workload, trust and interaction quality between operators of the same team in tasks with heterogeneous information loss. Fig. 7.30 shows

Table 7.14: Results of subjective scales with relationships between levels of information loss. The relationships are based on mean ranks obtained through Friedman tests. The symbol * denotes a significant difference ($p < 0.05$) and the symbol ** denotes a marginally significant difference ($p < 0.10$). The symbol $^-$ denotes negative scales where lower ranking is better.

Attributes	Relationship	$\chi^2(3)$	p-value
SART SUBJECTIVE SCALE			
Instability of Situation$^-$	Ho$_{HH}$ >He$_{HL}$ >He$_{LH}$ >Ho$_{LL}$	21.924	< 0.001
Complexity of Situation$^-$	Ho$_{HH}$ >He$_{HL}$ >He$_{LH}$ >Ho$_{LL}$	26.024	< 0.001
Variability of Situation$^-$	Ho$_{HH}$ >He$_{HL}$ >He$_{LH}$ >Ho$_{LL}$	27.862	< 0.001
Arousal	Ho$_{LL}$ >He$_{LH}$ >Ho$_{HH}$ >He$_{HL}$	18.850	< 0.001
Concentration of Attention	Ho$_{LL}$ >He$_{LH}$ >He$_{HL}$ >Ho$_{HH}$	16.088	< 0.001
Spare Mental Capacity	Ho$_{LL}$ >He$_{LH}$ >Ho$_{HH}$ >He$_{HL}$	10.112	0.018
Information Quantity	Ho$_{LL}$ >He$_{LH}$ >Ho$_{HH}$ >He$_{HL}$	7.014	0.071
Information Quality	Ho$_{LL}$ >He$_{LH}$ >He$_{HL}$ >Ho$_{HH}$	11.464	0.009
Familiarity with Situation	Ho$_{LL}$ >He$_{LH}$ >Ho$_{HH}$ >He$_{HL}$	6.949	0.074
NASA TLX SUBJECTIVE SCALE			
Mental Demand$^-$	Ho$_{HH}$ >He$_{HL}$ >He$_{LH}$ >Ho$_{LL}$	15.112	0.02
Physical Demand$^-$	Ho$_{HH}$=He$_{HL}$ >He$_{LH}$ >Ho$_{LL}$	9.089	0.028
Temporal Demand$^-$	not significant	5.447	0.142
Performance	Ho$_{LL}$ >He$_{LH}$ >He$_{HL}$ >Ho$_{HH}$	37.893	< 0.001
Effort$^-$	Ho$_{HH}$ >He$_{HL}$ >He$_{LH}$ >Ho$_{LL}$	23.053	< 0.001
Frustration$^-$	Ho$_{HH}$ >He$_{HL}$ >He$_{LH}$ >Ho$_{LL}$	21.124	< 0.001
TRUST SUBJECTIVE SCALE			
Competence	Ho$_{LL}$ >He$_{LH}$ >He$_{HL}$ >Ho$_{HH}$	31.461	< 0.001
Predictability	Ho$_{LL}$ >He$_{LH}$ >He$_{HL}$ >Ho$_{HH}$	31.644	< 0.001
Reliability	Ho$_{LL}$ >He$_{LH}$ >He$_{HL}$ >Ho$_{HH}$	33.737	< 0.001
Faith	Ho$_{LL}$ >He$_{LH}$ >He$_{HL}$ >Ho$_{HH}$	31.210	< 0.001
Overall Trust	Ho$_{LL}$ >He$_{LH}$ >He$_{HL}$ >Ho$_{HH}$	35.083	< 0.001
Accuracy	Ho$_{LL}$ >He$_{LH}$ >He$_{HL}$ >Ho$_{HH}$	29.254	< 0.001
INTERACTION SUBJECTIVE SCALE			
Teammate's Intent	not significant	5.880	0.118
Teammate's Action	Ho$_{LL}$ >Ho$_{HH}$ >He$_{HL}$ >He$_{LH}$	7.718	0.052
Task Progress	Ho$_{LL}$ >He$_{LH}$ >Ho$_{HH}$ >He$_{HL}$	18.854	< 0.001
Robot Status	Ho$_{LL}$ >He$_{LH}$ >Ho$_{HH}$ >He$_{HL}$	34.420	< 0.001
Information Clarity	Ho$_{LL}$ >Ho$_{HH}$ >He$_{LH}$ >He$_{HL}$	6.703	0.082

which information loss cases were preferred by each operator. I used the Borda count [20] to calculate the overall ranking. Table 7.16 shows the results of the Borda count for each

Table 7.15: Results of objective metrics with relationships between levels of information loss. The relationships are based on mean ranks obtained through Friedman tests. The symbol * denotes a significant difference ($p < 0.05$) and the symbol ** denotes a marginally significant difference ($p < 0.10$). The symbol $^{-}$ denotes negative scales where lower ranking is better.

Attributes	Relationship	$\chi^2(3)$	p-value
PERFORMANCE OBJECTIVE SCALE			
Time Taken for the task	$\text{Ho}_{HH} > \text{He}_{HL} = \text{He}_{LH} > \text{Ho}_{LL}$	11.803	0.008
Number of Interactions	$\text{He}_{LH} > \text{Ho}_{HH} > \text{Ho}_{LL} > \text{He}_{HL}$	17.258	0.008
Time gap between interactions	$\text{Ho}_{HH} > \text{He}_{HL} > \text{He}_{LH} > \text{Ho}_{LL}$	11.220	0.011

Table 7.16: Ranking scores based on the Borda count. The gray cells indicate the best case for each type of ranking.

Borda Count	Ho_{LL}	Ho_{HH}	He_{LH}	He_{HL}
Based on Collected Data Ranking (Tables 7.14 & 7.15)	104	36.5	74.5	45
Based on Preference Data Ranking (Fig. 7.30)	77	29	52	42

category.

Pilot and Main Study: Comparative Analysis

Pilot Study Data Analysis. Tables 7.5-7.29 and Figures 7.22-7.28 indicate that, with the increase in information loss, the workload experienced by the operator increases while performance degrades. I compared the number of interactions made with each level of information loss, and found no significant difference. I also recorded the time interval between interactions. The box plot of the median values (shown in Fig. 7.31) indicates a significant increase ($\chi^2(1) = 30.486$, $p < 0.001$) in time waited between interactions, according to the well-known *waiting strategy* observed in user studies with traditional tele-operation and remote interaction systems [62].

Pilot Study Behavioral Analysis. I observed the behaviour of the operators during and after each session. Two operators (out of 20) chose to stop their session with 2 s and 2.5 s of information loss. They reported that they had reached their ability to handle

Table 7.17: Results of subjective scales with attribute comparison between operators of the same team. The comparisons are based on mean ranks obtained through the Friedman test. The grey cells represent significant differences between operators in the same team.

Attributes	**Homogeneous IL**				**Heterogeneous IL**	
	Ho$_{LL}$		**Ho**$_{HH}$			
	χ^2	p**-value**	χ^2	p**-value**	χ^2	p**-value**
SART SUBJECTIVE SCALE						
Instability of Situation	0	1	0	1	0.6	0.439
Complexity of Situation	3	0.083	0	1	0.529	0.467
Variability of Situation	2.667	0.102	1.286	0.257	1.143	0.285
Arousal	0.5	0.480	0.667	0.414	7.143	0.008
Concentration of Attention	2.667	0.102	0.667	0.414	2.778	0.096
Spare Mental Capacity	0.2	0.655	1.286	0.257	5.444	0.02
Information Quantity	0.5	0.480	0.5	0.480	1.667	0.197
Information Quality	0.5	0.480	0.143	0.750	5.444	0.02
Familiarity with Situation	0.2	0.655	0	1	0.057	0.796
NASA TLX SUBJECTIVE SCALE						
Mental Demand	0	1	0.5	0.48	3.257	0.071
Physical Demand	0.333	0.564	0.111	0.739	1.143	0.285
Temporal Demand	1	0.317	0.143	0.705	0.077	0.782
Performance	2	0.157	0.111	0.739	7.143	0.008
Effort	0	1	0.2	0.655	5.444	0.02
Frustration	0.333	0.564	0	1	3.267	0.071
TRUST SUBJECTIVE SCALE						
Competence	0	1	1.8	0.180	9.308	0.002
Predictability	2	0.157	0	1	6.231	0.013
Reliability	0.333	0.564	2.667	0.102	6.231	0.013
Faith	0.333	0.564	0.667	0.414	3.769	0.052
Overall Trust	0	1	0.2	0.655	6.231	0.013
Accuracy	0	1	0.2	0.655	5.444	0.02
INTERACTION SUBJECTIVE SCALE						
Teammate's Intent	0.667	0.414	0	1	0.057	0.795
Teammate's Action	1.8	0.180	0.143	0.705	0	1
Task Progress	0.333	0.564	2.667	0.102	2.579	0.108
Robot Status	0.667	0.414	0.4	0.527	5.333	0.021
Information Clarity	0.143	0.705	0.5	0.480	0.286	0.593

the high information loss. Eleven operators reported that they had reached their limit of frustration at 2.5 s, but nevertheless chose to continue because of their *never give up*

Table 7.18: Results of quantitative scales with attribute comparison between operators of the same team. The comparisons are based on mean ranks obtained through the Friedman test. The grey cells represent significant differences between operators in the same team.

Attributes	**Homogeneous IL**				**Heterogeneous IL**	
	Ho$_{LL}$		**Ho$_{HH}$**			
	χ^2	p**-value**	χ^2	p**-value**	χ^2	p**-value**
PERFORMANCE OBJECTIVE SCALE						
Number of Interactions	0.111	0.739	1	0.317	0	1
Time gap between interactions	0.4	0.527	1.6	0.206	0	1

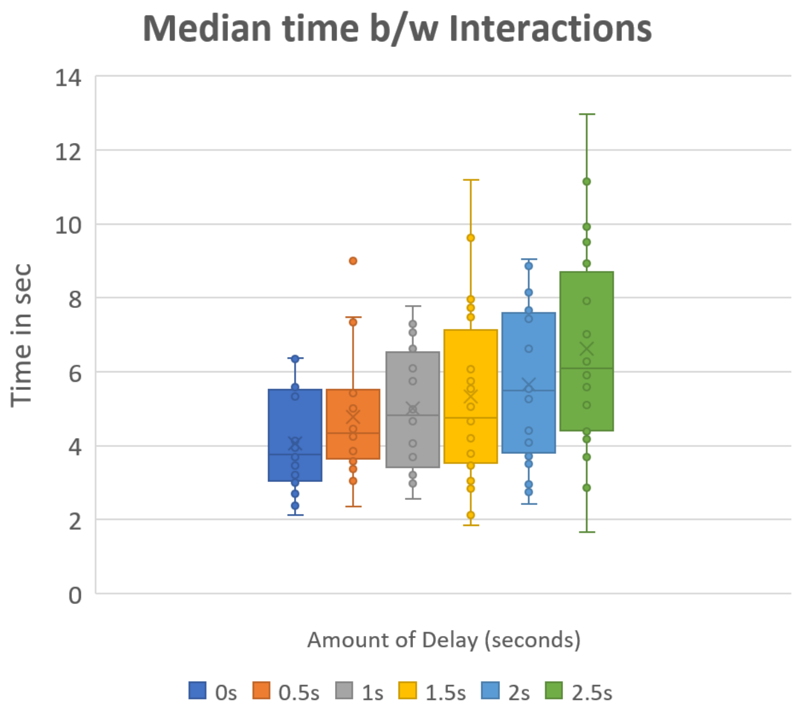


Figure 7.31: Box plot of the recorded time gap between each interaction for each operator.

attitude and their willingness to help my research. Seven operators reported that they could have handled higher than 2.5 s of loss because of their past experience with laggy systems and internet. As for the discomfort experienced by the operators, three operators started experiencing discomfort with 1 s of information loss; four operators with values over 1.5 s; three operators with information loss over 2 s; and six operators with information loss over 2.5 s. The reported discomfort included a slight headache and fatigue in their eyes. As a part of the exit interview for the pilot study, I asked the participants if the task order assigned to them impacted their performance in the study. The participants in the increasing order of information loss reported that the increase in loss made them ready for the next task and they expected the loss to increase. They reported that, with each task, the familiarity with experiencing loss was increasing, causing them to be better trained at handling it. All the participants in this category reported that they would have been more frustrated if the task ordering was reversed and they would be most frustrated if they had to experience the maximum information loss in the first task. However, the participants in the decreasing order of information loss reported that they would have been more frustrated if the information loss were increasing in each task. All the participants in this cohort reported that, as the loss was decreasing, they knew the worst was over and the tasks will only get easier from there on. I call this the *count one's blessing* phenomenon: the participants preferred and defended their task order, assuming that the reverse order would only harm their performance and interaction quality.

Main Study Data Analysis. Table 7.16 shows that Ho_{LL} is the best information loss case both in terms of usability preference and according to the data collected during the user study. This supports my hypotheses $\mathbf{H}_{IL}\mathbf{1}$ and $\mathbf{H}_{IL}\mathbf{2}$ that low homogeneous information loss is the best overall case. The He_{LH} case is the next best choice for the participants, indicating preference for low personal information loss. This supports hypothesis, $\mathbf{H}_{IL}\mathbf{3}$. The He_{HL} case is the third choice, showing that either operator experiencing low loss is still better than both operators experiencing high information loss. This supports hypothesis $\mathbf{H}_{IL}\mathbf{4}$.

Main Study Behavioral Analysis. I also observed the behaviour of the operators during and after the sessions. Based on the preference shown in Fig. 7.30, I could categorize the participants in four typologies. (a) *The Egocentrics*: ten participants gave higher preference to the tasks with low information loss, and lower preference to the tasks with high information loss. However, when they had to rank their preference between the options of choosing low and high information loss for themselves and give the other to their teammate, the participants opted for low information loss even though that meant that their teammate might get more frustrated by experiencing higher loss. (b) *The Altruists*: five participants preferred to handle high information loss so that their teammate might face lower levels of frustration while interacting with a low information loss. These participants, the altruists, reported that they were confident in their ability to handle high information loss, and with their teammate experiencing low information loss their chances of completing the task might increase. (c) *The Egalitarians*: four participants preferred homogeneous loss over heterogeneous loss, even if that means that both operators would have to experience a high information loss. These participants reported that, with homogeneous information loss, they could actively interact with their teammate and handle equal workload, which they did not experience in tasks with heterogeneous information loss. (d) *The Thinker*: one participant preferred high information loss over low information loss. This participant reported that high information loss provided more time to think before making the next step and could interact more with the fellow teammate while doing so.

On the Out-of-the-Loop Performance Problem. Tables 7.17 and 7.18 show that the participants experienced unbalanced awareness, workload, trust and interaction quality, while engaging in the tasks with heterogeneous information loss. This imbalance indicates that the operator experiencing high information loss will go *out of the loop* [66, 84]. However, the interaction quality scales show that the significant difference in information awareness is observed only for the robot-level information and not on operator-level information. I conclude this as there was no loss or delay experienced in the communication channel for this user study; future work could investigate the impact of loss of communication between the operators.

7.5 Chapter Summary

In this chapter, I studied the effects of transparency, inter-human communication, and information loss on multi-human multi-robot interaction. I first performed a study of the most effective interface elements to support information transparency and inter-operator transparency. I analyzed the usability of my interface through a user study with 14 operators measuring awareness, workload, trust, and interaction efficiency. The findings of the user study indicated mixed transparency as the best transparency mode and mixed communication as the best communication mode.

I then studied the effects of information loss on the performance of the operators. I performed two user studies. The first, a pilot study, aimed to identify the amount of information loss that can be considered noticeable but bearable for the average operator, and which amount of information loss is unbearable. Using the result of this study, I performed a thorough exploration of the role of information loss in multi-operator scenarios, comparing heterogeneous and homogeneous cases. I derived a set of behavioral typologies of users, revealing that remote interaction must consider personal preferences and individual attitude when forming groups of operators.

Chapter 8

Conclusion and Future Work

The future of humanity is filled with mobile robots. We envision mobile robots to aid human operators in complex humanitarian missions, including exploring underwater caves and the depths of the universe. Many researchers made successful contributions towards this dream by investigating methods for controlling, understanding, and communicating with the robots. The research in this domain extends from applications to teleoperation systems, disaster management systems, and social robotic systems. The research scope is widening, and multi-robot systems are taking a central place. Multi-robot systems are inherently complex in nature because of the potentially large number of units involved. The interaction with a multi-robot system is likely to exceed the limits of the span of apprehension of any individual human operator. A solution to this problem is to include more than one operator in the interaction.

However, with multiple human operators, additional challenges arise. These include granularity of control, operator engagement, operator-level information transparency and inter-human coordination. Beyond human-robot interaction [21, 233], these challenges exists in domains where more than one human is in the loop, including human-computer systems [91, 214, 246], human-machine systems [93, 106, 228], supervisory control systems [26, 151], and social interaction systems [12, 145, 181].

The ideas that I propose have been investigated also in these domains and my research confirms the benefits I discussed in the discipline of multi-human multi-robot interaction. One such methods includes identifying the correct granularity of control. Granularity of control is a major paradigm that improves operator engagement [65] and employing higher granularity of control leads to lower workload experienced by the human operator [63, 72]. However, while interacting with multiple robots, using only high granularity of control is not sufficient as it lacks the capability of fine-grained control to perform corrective maneuvers. A mixed granularity of control can enable an operator to control both the global goal and the local goals of multiple robots, improving the performance of the operator while experiencing lower workload.

Depending on the workload, the operator will experience mind wavering [84] and lower engagement [31, 185]. The negative impact on the engagement of the operator and lack of awareness can cause the operator to go *out-of-the-loop* [27, 110]. Endsley [65] suggests that the operators prefer to be constantly engaged with the tasks, rather than switching from inactivity to a sudden moment of high load. The user studies in my work confirm the benefit of keeping operator engaged.

Lack of awareness occurs due to lack of information [54, 161, 204] and lack of coordination [44, 102, 230] between human operators. The information transparency provides awareness about the situation, positively impacting the performance of the operator [64]. Lee [133] proposes that the operators are exposed to information only when they request it instead of information be constantly present on the interface. These results are applicable to systems with multiple operators interacting with multiple robots. With limited information available, the operators better focus on the task at hand, reducing the complexity of the situation. Similarly for operator coordination, operators prefer to verbally communicate their general intentions in comparison to conveying each actions, simplifying the information exchange between the operators [54].

Besides the literature on the classical human-human systems, little attention has been given to studies involving multiple human operators interacting with multiple mobile robots. Hence, extending the *state-of-the-art*, this thesis provides scientific and technological insight concerning these challenges and their impact on the performance of the operators, measured in terms of awareness, workload, trust, and the quality of interaction.

The first contribution of this work was a novel mixed-reality interface with mixed granularity of control. This interface enables an operator to control the high-level and low-level goals of the robots. With environment- or team-oriented control, the operators can indicate high-level goals, such as moving an object, and the robots autonomously carry out the task. The operators can also manipulate individual robots or perform corrective maneuvers using low-level robot control. Through a user study with 10 participants, I showed the effectiveness of mixed granularity of control over a single granularity of control. Using mixed granularity of control, the performance of the operators improved, while their workload diminished.

The first study involved a single operator interacting with multiple robots. With multiple operators interacting with multiple robots, the operators experience unbalanced workload and inhomogeneous awareness causing them to go *out-of-the-loop*. I hypothesized that with mixed granularity of control the operators share the workload and become equally aware. I investigated the impact of mixed granularity of control on multiple operators' engagement. Through a user study involving 28 participants, I demonstrated the use of mixed granularity of control over a single granularity of control, i.e., generalized control of the task over the specialized control of the task. With mixed granularity of control, the operators reported to be actively interacting and did not feel out-of-the-loop, while bearing balanced workload, awareness and trust in the system.

In addition to methods to control robots, the operators should also be able to understand the robots. Transparency is a key property of an interface and directly affects the performance of the operator. I introduced transparency features to enable human operators to understand robot-level and operator-level information. I categorized the transparency features, based on the interface field of view, as peripheral transparency, central transparency, and mixed transparency. In peripheral transparency, the operator access information in the interface's periphery; in central transparency, the operator access information in the central region of the interface. In mixed transparency, the operator access features of both peripheral and central transparency. With a user study involving 18 participants, the participants reported mixed transparency as the best mode, in terms of reported metrics and preference data, followed by central transparency as second choice.

Another aspect of transparency between operators is inter-human communication. Communication is key for effective teamwork, be it between humans or between humans and robots. Humans communicate directly through verbal communication or indirectly representing their actions and intentions using the interface, or with a mix of both. I compared the impact of indirect communication with direct communication and mixed communication. Through a user study with 18 participants, I found mixed communication to be the best mode to allow users to effectively exchange operator-level information and robot-level information.

Besides proximal interaction, operators should also be able to remotely interact with robots. I designed a cloud-based interface to allow multiple operators to remotely interact with multiple robots. I investigated the effects of the transparency modes and communication modes on the performance of the operator and compared the results of remote interaction with those of proximal interactions. With a user study including 28 users, I noted that the results of remote interaction were in line with that of proximal interaction with mixed transparency and mixed communication as the preferred modes of interaction.

However, the studies of remote interaction were limited to ideal conditions and in practical remote interaction systems information loss is inevitable. Information loss persists because of packet loss, bandwidth limitations, or distance between the geographical locations of the operators and the robots. I studied the impact of information loss on the performance of operators remotely interacting with multiple mobile robots. I categorized information loss into homogeneous and heterogeneous to study its impact on the operators. I split the user study in two parts, the pilot study and the main study. In the *pilot study*, I analyzed the impact of information loss on a single operator. In the *main study*, I assessed the impact of homogeneous and heterogeneous information loss on multiple operators' performance. Through a user study with 20 participants, I reported homogeneous low loss as the most favorable, although practically not always feasible. I also reported a significant difference in the awareness, workload, trust, and interaction quality among the operators of the same team due to heterogeneous information loss, causing the operator with relatively higher information loss to go out-of-the-loop.

The results of my work allow me to compile a list of guidelines that will positively affect the performance of the human operator in multi-human multi-robot interaction. I list the guidelines as follows.

1. The operators should be able to have a *mixed granularity of control* over the robots. An operator should be able to interact with an individual robot, a subset of robots, and influence the environment. With mixed granularity of control, all the operators should be equally *engaged* in the task while sharing equal awareness and workload with other operators.

2. The interface should provide robot-level and operator-level *transparency* to all the operators. Operators prefer to access information in the central field-of-view of the interface over the peripheral field-of-view.

3. Operators should be able to directly and indirectly engage in interaction. Operators prefer direct communication to exchange operator-level information and have better

trust on robots with indirect communication. In absence of direct communication, the operators should be able to indirectly understand the intent and actions of other operators through the information transparency.

4. With different information loss in remote interaction between operators, the operators generally prefer experiencing low information loss even if that means a high information loss for their counter part. Different operators have different preference in remote interaction and their preference should be considered while teaming with other operators.

8.1 Future Work

Future work is possible in several directions. One direction is to identify an association of the role a human play in the system with an interface, i.e., to investigate the appropriate interface that would suit the role of the human. These roles can be classified as supervisor, operator, teammate, mechanic, and bystander as discussed by Yanco and Dury [242]. The interface, in my work, was tested with participants interacting as an operator, however a combination of interfaces present in the system may enable operators to assume a particular role or share the roles. A possible extension to the problem statement may include a human present in the same environment and another human remotely interacts with the system. In this test case, the human sharing the environment with the robots may assume the role of an operator, while the human remotely interacting may behave as a supervisor.

Another direction for future work may include bringing heterogeneity in the testing conditions. In user studies for transparency and communication in proximal and remote interaction, I assumed both operators would possess the same ability of understanding the robots and other operators. However, an interesting problem would be to study the behaviour of the operators having different interface capabilities. An operator may be equipped with mixed transparency, while another operator has no information transparency. Such instances may occur in complex missions when an operator experiences system failures and has to rely on their teammate for robot-level information. I presume a similar outcome to that of the operator engagement user study, i.e., inequality in transparency and communication capability, may cause an operator to go out-of-the-loop.

A third direction for future work may include adding machine learning to the interaction. With machine learning, the interface can learn to automatically remove features that are not being used by the operator and reduce the information clutter, positively impacting the cognitive workload of the operator. By learning the human inputs, the interface can recommend actions to the operator and help achieve better performance, causing the operators to trust the interface more. Machine learning can also help create predictive features to cope with information loss. The interface could also monitor and diagnose system faults, making operators better aware of possible failure modes of the robots and act accordingly.

Bibliography

[1] iRobot's Roomba robot vacuum. https://www.irobot.com/roomba. Accessed:.

[2] Vuforia augmented reality. http://vuforia.com. Accessed:.

[3] ADMONI, H., AND SCASSELLATI, B. Social eye gaze in human-robot interaction: a review. *Journal of Human-Robot Interaction 6*, 1 (2017), 25–63.

[4] ALLEN, K., BERGIN, R., AND PICKAR, K. Exploring trust, group satisfaction, and performance in geographically dispersed and co-located university technology commercialization teams. In *VentureWell. Proceedings of Open, the Annual Conference* (2004), National Collegiate Inventors & Innovators Alliance, p. 201.

[5] ALONSO-MORA, J., HAEGELI LOHAUS, S., LEEMANN, P., SIEGWART, R., AND BEARDSLEY, P. Gesture based human - Multi-robot swarm interaction and its application to an interactive display. In *2015 IEEE International Conference on Robotics and Automation (ICRA)* (Seattle, WA, USA, May 2015), IEEE, pp. 5948–5953.

[6] ANDERSEN, R. S., MADSEN, O., MOESLUND, T. B., AND AMOR, H. B. Projecting robot intentions into human environments. In *2016 25th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)* (New York, NY, USA, Aug. 2016), IEEE, pp. 294–301.

[7] ARAI, T., PAGELLO, E., PARKER, L. E., ET AL. Advances in multi-robot systems. *IEEE Transactions on robotics and automation 18*, 5 (2002), 655–661.

[8] ASIMOV, I. *I, robot*. Spectra, 2004.

[9] AYANIAN, N., SPIELBERG, A., ARBESFELD, M., STRAUSS, J., AND RUS, D. Controlling a team of robots with a single input. In *Robotics and Automation (ICRA), 2014 IEEE International Conference on* (2014), IEEE, pp. 1755–1762.

[10] BAJCSY, A., HERBERT, S. L., FRIDOVICH-KEIL, D., FISAC, J. F., DEGLURKAR, S., DRAGAN, A. D., AND TOMLIN, C. J. A Scalable Framework For Real-Time Multi-Robot, Multi-Human Collision Avoidance. *arXiv:1811.05929 [cs]* (Nov. 2018). arXiv: 1811.05929.

[11] BAKER, M., CASEY, R., KEYES, B., AND YANCO, H. A. Improved interfaces for human-robot interaction in urban search and rescue. In *2004 IEEE International Conference on Systems, Man and Cybernetics (IEEE Cat. No. 04CH37583)* (2004), vol. 3, IEEE, pp. 2960–2965.

[12] BARON, R. A., AND BYRNE, D. *Social psychology: Understanding human interaction*. Allyn & Bacon, 1987.

[13] BARTNECK, C., KULIĆ, D., CROFT, E., AND ZOGHBI, S. Measurement Instruments for the Anthropomorphism, Animacy, Likeability, Perceived Intelligence, and Perceived Safety of Robots. *International Journal of Social Robotics 1*, 1 (Jan. 2009), 71–81.

[14] BASHYAL, S., AND VENAYAGAMOORTHY, G. K. Human swarm interaction for radiation source search and localization. IEEE, pp. 1–8.

[15] BEER, R. D., RIETH, C. A., TRAN, R., AND COOK, M. B. Framework for Multi-Human Multi-Robot Interaction: Impact of Operational Context and Team Configuration on Interaction Task Demands. *2017 AAAI Spring Symposium Series* (2017), 8.

[16] BENFORD, S., AND GIANNACHI, G. *Performing mixed reality*. The MIT Press, 2011.

[17] BHASKARA, A., SKINNER, M., AND LOFT, S. Agent Transparency: A Review of Current Theory and Evidence. *IEEE Transactions on Human-Machine Systems* (2020), 1–10.

[18] BHATTACHARYYA, R. P., PHILLIPS, D. J., WULFE, B., MORTON, J., KUEFLER, A., AND KOCHENDERFER, M. J. Multi-agent imitation learning for driving

simulation. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (2018), IEEE, pp. 1534–1539.

[19] BISK, Y., YURET, D., AND MARCU, D. Natural language communication with robots. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies* (2016), pp. 751–761.

[20] BLACK, D. Partial justification of the borda count. *Public Choice* (1976), 1–15.

[21] BOUCHER, J.-D., PATTACINI, U., LELONG, A., BAILLY, G., ELISEI, F., FAGEL, S., DOMINEY, P. F., AND VENTRE-DOMINEY, J. I reach faster when i see you look: gaze effects in human–human and human–robot face-to-face cooperation. *Frontiers in neurorobotics 6* (2012), 3.

[22] BRAMBILLA, M., FERRANTE, E., BIRATTARI, M., AND DORIGO, M. Swarm robotics: A review from the swarm engineering perspective. *Swarm Intelligence 7*, 1 (2013), 1–41.

[23] BREAZEAL, C., KIDD, C. D., THOMAZ, A. L., HOFFMAN, G., AND BERLIN, M. Effects of nonverbal communication on efficiency and robustness in human-robot teamwork. In *2005 IEEE/RSJ international conference on intelligent robots and systems* (2005), IEEE, pp. 708–713.

[24] BUTERS, T. M., BATEMAN, P. W., ROBINSON, T., BELTON, D., DIXON, K. W., AND CROSS, A. T. Methodological ambiguity and inconsistency constrain unmanned aerial vehicles as a silver bullet for monitoring ecological restoration. *Remote Sensing 11*, 10 (2019), 1180.

[25] CACACE, J., FINZI, A., AND LIPPIELLO, V. Implicit robot selection for human multi-robot interaction in Search and Rescue missions. In *2016 25th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)* (New York, NY, USA, Aug. 2016), IEEE, pp. 803–808.

[26] CAI, K., ZHANG, R., AND WONHAM, W. Relative observability and coobservability of timed discrete-event systems. *IEEE Transactions on Automatic Control 61*, 11 (2015), 3382–3395.

[27] CALHOUN, G. L., AND DRAPER, M. H. 11. multi-sensory interfaces for remotely operated vehicles. In *Human factors of remotely operated vehicles*. Emerald Group Publishing Limited, 2006.

[28] CAMPBELL, D., GONZALEZ, F., AND COPPIN, G. The Effect of Autonomy Transparency in Human-Robot Interactions: A Preliminary Study on Operator Cognitive Workload and Situation Awareness in Multiple Heterogeneous UAV Management. 10.

[29] CAPELLI, B., SECCHI, C., AND SABATTINI, L. Communication Through Motion: Legibility of Multi-Robot Systems. In *2019 International Symposium on Multi-Robot and Multi-Agent Systems (MRS)* (New Brunswick, NJ, USA, Aug. 2019), IEEE, pp. 126–132.

[30] CAPPO, E. A., DESAI, A., COLLINS, M., AND MICHAEL, N. Online planning for human–multi-robot interactive theatrical performance. *Autonomous Robots 42*, 8 (2018), 1771–1786.

[31] CELIKTUTAN, O., SKORDOS, E., AND GUNES, H. Multimodal human-human-robot interactions (mhhri) dataset for studying personality and engagement. *IEEE Transactions on Affective Computing 10*, 4 (2017), 484–497.

[32] CHADALAVADA, R. T., ANDREASSON, H., KRUG, R., AND LILIENTHAL, A. J. That's on my mind! robot to human intention communication through on-board projection on shared floor space. In *2015 European Conference on Mobile Robots (ECMR)* (Lincoln, Sept. 2015), IEEE, pp. 1–6.

[33] CHAKRABORTI, T., KULKARNI, A., SREEDHARAN, S., SMITH, D. E., AND KAMBHAMPATI, S. Explicability? Legibility? Predictability? Transparency? Privacy? Security? The Emerging Landscape of Interpretable Agent Behavior. 11.

[34] CHE, Y., OKAMURA, A. M., AND SADIGH, D. Efficient and trustworthy social navigation via explicit and implicit robot–human communication. *IEEE Transactions on Robotics* (2020).

[35] CHEN, J. Y., AND BARNES, M. J. Human–agent teaming for multirobot control: A review of human factors issues. *IEEE Transactions on Human-Machine Systems 44*, 1 (2014), 13–29.

[36] CHEN, J. Y., AND BARNES, M. J. Agent Transparency for Human-Agent Teaming Effectiveness. In *2015 IEEE International Conference on Systems, Man, and Cybernetics* (Kowloon Tong, Hong Kong, Oct. 2015), IEEE, pp. 1381–1385.

[37] CHEN, J. Y., DURLACH, P. J., SLOAN, J. A., AND BOWENS, L. D. Human–robot interaction in the context of simulated route reconnaissance missions. *Military Psychology 20*, 3 (2008), 135–149.

[38] CHEN, J. Y., PROCCI, K., BOYCE, M., WRIGHT, J., GARCIA, A., AND BARNES, M. Situation Awareness-Based Agent Transparency:. Tech. rep., Defense Technical Information Center, Fort Belvoir, VA, Apr. 2014.

[39] CHEN, J. Y. C., HAAS, E. C., AND BARNES, M. J. Human Performance Issues and User Interface Design for Teleoperated Robots. *IEEE Transactions on Systems, Man and Cybernetics, Part C (Applications and Reviews) 37*, 6 (Nov. 2007), 1231–1245.

[40] CHEN, J. Y. C., LAKHMANI, S. G., STOWERS, K., SELKOWITZ, A. R., WRIGHT, J. L., AND BARNES, M. Situation awareness-based agent transparency and human-autonomy teaming effectiveness. *Theoretical Issues in Ergonomics Science 19*, 3 (May 2018), 259–282.

[41] CHEN, M., ZHANG, P., CHEN, X., ZHOU, Y., LI, F., AND DU, G. A Human-swarm Interaction Method Based on Augmented Reality. In *2018 WRC Symposium on Advanced Robotics and Automation (WRC SARA)* (Beijing, Aug. 2018), IEEE, pp. 108–114.

[42] CHEN, T., CAMPBELL, D., GONZALEZ, L. F., AND COPPIN, G. Increasing Autonomy Transparency through capability communication in multiple heterogeneous UAV management. In *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (Hamburg, Germany, Sept. 2015), IEEE, pp. 2434–2439.

[43] CHEN TUN CHOU, JIUN-YI LI, MING-FANG CHANG, AND LI CHEN FU. Multi-robot cooperation based human tracking system using Laser Range Finder. In *2011 IEEE International Conference on Robotics and Automation* (Shanghai, China, May 2011), IEEE, pp. 532–537.

[44] CHENG, Y., HE, F., WU, Y., AND ZHANG, D. Meta-operation conflict resolution for human–human interaction in collaborative feature-based cad systems. *Cluster Computing 19*, 1 (2016), 237–253.

[45] CHEUNG, Y., AND CHUNG, J. H. Semi-Autonomous Control of Single-Master Multi-Slave Teleoperation of Heterogeneous Robots for Multi-Task Multi-Target Pairing. *International Journal of Control and Automation 4*, 3 (2011), 17.

[46] CHIEN, S.-Y., LEWIS, M., SYCARA, K., KUMRU, A., AND LIU, J.-S. Influence of Culture, Transparency, Trust, and Degree of Automation on Automation Use. *IEEE Transactions on Human-Machine Systems* (2019), 1–10.

[47] CLAES, D., AND TUYLS, K. Multi robot collision avoidance in a shared workspace. *Autonomous Robots 42*, 8 (Dec. 2018), 1749–1770.

[48] COLLETT, T., AND MACDONALD, B. Developer oriented visualization of a robot program: An augmented reality approach. In *Proc of the 2006 ACM Conference on Human-Robotic Interaction* (2006), pp. 2–4.

[49] COLLETT, T. H. J., AND MACDONALD, B. A. An augmented reality debugging system for mobile robot software engineers. *JOURNAL OF SOFTWARE ENGINEERING IN ROBOTICS 1*, 1 (2010), 18–32.

[50] DAILY, M., CHO, Y., MARTIN, K., AND PAYTON, D. World embedded interfaces for human-robot interaction. In *System Sciences, 2003. Proceedings of the 36th Annual Hawaii International Conference on* (2003), IEEE, pp. 6–pp.

[51] DAILY, M., CHO, Y., MARTIN, K., AND PAYTON, D. World embedded interfaces for human-robot interaction. In *36th Annual Hawaii International Conference on System Sciences, 2003. Proceedings of the* (2003), IEEE, pp. 6–pp.

[52] DARDONA, T., ESLAMIAN, S., REISNER, L. A., AND PANDYA, A. Remote Presence: Development and Usability Evaluation of a Head-Mounted Display for Camera Control on the da Vinci Surgical System. *Robotics 8*, 2 (Apr. 2019), 31.

[53] DARKEN, R. P., AND PETERSON, B. Spatial orientation, wayfinding, and representation., 2014.

[54] DEMIR, M., MCNEESE, N. J., AND COOKE, N. J. Team situation awareness within the context of human-autonomy teaming. *Cognitive Systems Research 46* (2017), 3–12.

[55] DENKENBERGER, J. S., DRISCOLL, C. T., EFFLER, S. W., O'DONNELL, D. M., AND MATTHEWS, D. A. Comparison of an urban lake targeted for rehabilitation

and a reference lake based on robotic monitoring. *Lake and Reservoir Management 23*, 1 (2007), 11–26.

[56] DIAS, M. B. Dynamically Formed Human-Robot Teams Performing Coordinated Tasks. 9.

[57] DIAZ-MERCADO, Y., LEE, S. G., AND EGERSTEDT, M. Distributed dynamic density coverage for human-swarm interactions. In *American Control Conference (ACC), 2015* (2015), IEEE, pp. 353–358.

[58] DIMITOGLOU, G. Telepresence: Evaluation of Robot Stand-Ins for Remote Student Learning. 15.

[59] DO, N. D., YAMASHINA, Y., AND NAMERIKAWA, T. Multiple Cooperative Bilateral Teleoperation with Time-Varying Delay. *SICE Journal of Control, Measurement, and System Integration 4*, 2 (2011), 89–96.

[60] DONG GUN LEE, GUN RAE CHO, MIN SU LEE, BYUNG-SU KIM, SEHOON OH, AND HYOUNG IL SON. Human-centered evaluation of multi-user teleoperation for mobile manipulator in unmanned offshore plants. In *2013 IEEE/RSJ International Conference on Intelligent Robots and Systems* (Tokyo, Nov. 2013), IEEE, pp. 5431–5438.

[61] DUFFY, B. R. Anthropomorphism and the social robot. *Robotics and autonomous systems 42*, 3-4 (2003), 177–190.

[62] ELLIS, S. R., MANIA, K., ADELSTEIN, B. D., AND HILL, M. I. Generalizeability of latency detection in a variety of virtual environments. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (2004), vol. 48, SAGE Publications Sage CA: Los Angeles, CA, pp. 2632–2636.

[63] ENDSLEY, M. Autonomous horizons: System 'autonomy'in the air force–a path to the future: Volume i: Human autonomy teaming. *US Department of the Air Force, Washington* (2015).

[64] ENDSLEY, M., AND BOLTÉ, B. J. Dg (2003). designing for situation awareness: An approach to user-centered design.

[65] ENDSLEY, M. R. From here to autonomy: lessons learned from human–automation research. *Human factors 59*, 1 (2017), 5–27.

[66] ENDSLEY, M. R., AND KIRIS, E. O. The out-of-the-loop performance problem and level of control in automation. *Human factors 37*, 2 (1995), 381–394.

[67] ENGINE, U. G. Unity game engine-official site. *Online][Cited: October 9, 2008.] http://unity3d. com* (2008), 1534–4320.

[68] ESFAHLANI, S. S. Mixed reality and remote sensing application of unmanned aerial vehicle in fire and smoke detection. *Journal of Industrial Information Integration* (May 2019), S2452414X18300773.

[69] FELZMANN, H., FOSCH-VILLARONGA, E., LUTZ, C., AND TAMO-LARRIEUX, A. Robots and Transparency: The Multiple Dimensions of Transparency in the Context of Robot Technologies. *IEEE Robotics & Automation Magazine 26*, 2 (June 2019), 71–78.

[70] FERREIRA, L. R. N., AND PEREIRA, L. T. Immersive Mobile Telepresence Systems: A Systematic Literature Review. 16.

[71] FETH, D., TRAN, B. A., GROTEN, R., PEER, A., AND BUSS, M. Shared-Control Paradigms in Multi-Operator-Single-Robot Teleoperation. In *Human Centered Robot Systems*, R. Dillmann, D. Vernon, Y. Nakamura, S. Schaal, H. Ritter, G. Sagerer, R. Dillmann, and M. Buss, Eds., vol. 6. Springer Berlin Heidelberg, Berlin, Heidelberg, 2009, pp. 53–62. Series Title: Cognitive Systems Monographs.

[72] FORCE, U. A. Autonomous horizons. *Washington, DC: US Air Force Office of the Chief Scientist* (2015).

[73] FRANK, J. A., KRISHNAMOORTHY, S. P., AND KAPILA, V. Toward mobile mixed-reality interaction with multi-robot systems. *IEEE Robotics and Automation Letters 2*, 4 (2017), 1901–1908.

[74] FREEDY, A., SERT, O., FREEDY, E., MCDONOUGH, J., WELTMAN, G., TAMBE, M., GUPTA, T., GRAYSON, W., AND CABRERA, P. Multiagent Adjustable Autonomy Framework (MAAF) for multi-robot, multi-human teams. In *2008 International Symposium on Collaborative Technologies and Systems* (Irvine, CA, USA, May 2008), IEEE, pp. 498–505.

[75] FRIEDMAN, M. The use of ranks to avoid the assumption of normality implicit in the analysis of variance. *Journal of the american statistical association 32*, 200 (1937), 675–701.

[76] GAO, F. Modeling teamwork of multi-human multi-agent teams. In *Proceedings of the 2013 conference on Computer supported cooperative work companion* (2013), pp. 47–50.

[77] GATES, B. A robot in every home. *Scientific American 296*, 1 (2007), 58–65.

[78] GERGEN, K. J. Social psychology as history. *Journal of personality and social psychology 26*, 2 (1973), 309.

[79] GHIRINGHELLI, F., GUZZI, J., DI CARO, G. A., CAGLIOTI, V., GAMBARDELLA, L. M., AND GIUSTI, A. Interactive augmented reality for understanding and analyzing multi-robot systems. In *Intelligent Robots and Systems (IROS 2014), 2014 IEEE/RSJ International Conference on* (2014), IEEE, pp. 1195–1201.

[80] GOERTZ, R. C., AND THOMPSON, W. M. Electronically controlled manipulator. *Nucleonics (US) Ceased publication 12* (1954).

[81] GOLDSMITH, D. Book review: Voyage to the milky way: the future of space exploration/tv books, 1999. *Sky and Telescope 98*, 5 (1999), 81.

[82] GOODRICH, M. A., PENDLETON, B., SUJIT, P. B., AND PINTO, J. Toward human interaction with bio-inspired robot teams. In *Systems, man, and cybernetics (smc), 2011 ieee international conference on* (2011), IEEE, pp. 2859–2864.

[83] GOODRICH, M. A., AND SCHULTZ, A. C. Human-Robot Interaction: A Survey. *Foundations and Trends® in Human-Computer Interaction 1*, 3 (2007), 203–275.

[84] GOURAUD, J., DELORME, A., AND BERBERIAN, B. Autopilot, mind wandering, and the out of the loop performance problem. *Frontiers in neuroscience 11* (2017), 541.

[85] GROMOV, B., GAMBARDELLA, L. M., AND DI CARO, G. A. Wearable multi-modal interface for human multi-robot interaction. In *2016 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR)* (2016), IEEE, pp. 240–245.

[86] GUZNOV, S., LYONS, J., PFAHLER, M., HEIRONIMUS, A., WOOLLEY, M., FRIEDMAN, J., AND NEIMEIER, A. Robot Transparency and Team Orientation Effects on Human–Robot Teaming. *International Journal of Human–Computer Interaction* (Oct. 2019), 1–11.

[87] HAMINS, A. P., BRYNER, N. P., JONES, A. W., KOEPKE, G. H., ET AL. Research roadmap for smart fire fighting. Tech. rep., 2015.

[88] HAN, J., SHAO, L., XU, D., AND SHOTTON, J. Enhanced computer vision with microsoft kinect sensor: A review. *IEEE transactions on cybernetics 43*, 5 (2013), 1318–1334.

[89] HART, S. G., AND STAVELAND, L. E. Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. In *Advances in Psychology*, vol. 52. Elsevier, 1988, pp. 139–183.

[90] HART, S. G., AND STAVELAND, L. E. Development of nasa-tlx (task load index): Results of empirical and theoretical research. In *Advances in psychology*, vol. 52. Elsevier, 1988, pp. 139–183.

[91] HE, F., AND HAN, S. A method and tool for human–human interaction and instant collaboration in cscw-based cad. *Computers in Industry 57*, 8-9 (2006), 740–751.

[92] HIGUERA, J. C. G., XU, A., SHKURTI, F., AND DUDEK, G. Socially-Driven Collective Path Planning for Robot Missions. In *2012 Ninth Conference on Computer and Robot Vision* (Toronto, Ontario, Canada, May 2012), IEEE, pp. 417–424.

[93] HOC, J.-M., AND LEMOINE, M.-P. Cognitive evaluation of human-human and human-machine cooperation modes in air traffic control. *The International Journal of Aviation Psychology 8*, 1 (1998), 1–32.

[94] HOKAYEM, P. F., AND SPONG, M. W. Bilateral teleoperation: An historical survey. *Automatica 42*, 12 (Dec. 2006), 2035–2057.

[95] HOLDCROFT, D. Forms of indirect communication: An outline. *Philosophy & Rhetoric* (1976), 147–161.

[96] HONG, A., BULTHOFF, H. H., AND SON, H. I. A visual and force feedback for multi-robot teleoperation in outdoor environments: A preliminary result. In *2013 IEEE International Conference on Robotics and Automation* (Karlsruhe, Germany, May 2013), IEEE, pp. 1471–1478.

[97] HONG, A., LEE, D. G., BÜLTHOFF, H. H., AND SON, H. I. Multimodal feedback for teleoperation of multiple mobile robots in an outdoor environment. *Journal on Multimodal User Interfaces 11*, 1 (Mar. 2017), 67–80.

[98] HOPPENSTEDT, B., WITTE, T., RUOF, J., KAMMERER, K., TICHY, M., REICHERT, M., AND PRYSS, R. Debugging Quadrocopter Trajectories in Mixed Reality. In *Augmented Reality, Virtual Reality, and Computer Graphics*, L. T. De Paolis and P. Bourdot, Eds., vol. 11614. Springer International Publishing, Cham, 2019, pp. 43–50.

[99] HUANG, K.-C., LI, J.-Y., AND FU, L.-C. Human-oriented navigation for service providing in home environment. In *Proceedings of SICE Annual Conference 2010* (2010), IEEE, pp. 1892–1897.

[100] HUSSEIN, A., AND ABBASS, H. Mixed initiative systems for human-swarm interaction: Opportunities and challenges. In *2018 2nd Annual Systems Modelling Conference (SMC)* (2018), IEEE, pp. 1–8.

[101] IQBAL, T., AND RIEK, L. D. Coordination Dynamics in Multihuman Multirobot Teams. *IEEE Robotics and Automation Letters 2*, 3 (July 2017), 1712–1717.

[102] ISBISTER, K., NAKANISHI, H., ISHIDA, T., AND NASS, C. Helper agent: Designing an assistant for human-human interaction in a virtual meeting space. In *Proceedings of the SIGCHI conference on Human factors in computing systems* (2000), pp. 57–64.

[103] JAKOBI, N., HUSBANDS, P., AND HARVEY, I. Noise and the reality gap: The use of simulation in evolutionary robotics. In *European Conference on Artificial Life* (1995), Springer, pp. 704–720.

[104] JANG, I., HU, J., ARVIN, F., CARRASCO, J., AND LENNOX, B. Omnipotent Virtual Giant for Remote Human-Swarm Interaction. *arXiv:1903.10064 [cs]* (Mar. 2019). arXiv: 1903.10064.

[105] JINGTAI LIU, LEI SUN, TAO CHEN, XINGBO HUANG, AND CHUNYING ZHAO. Competitive Multi-robot Teleoperation. In *Proceedings of the 2005 IEEE International Conference on Robotics and Automation* (Barcelona, Spain, 2005), IEEE, pp. 75–80.

[106] JOHANNSEN, G. Conceptual design of multi-human machine interfaces. *Control Engineering Practice 5*, 3 (1997), 349–361.

[107] JOHNSON, M., FELTOVICH, P. J., BRADSHAW, J. M., AND BUNCH, L. Human-robot coordination through dynamic regulation. In *2008 IEEE International Conference on Robotics and Automation* (2008), IEEE, pp. 2159–2164.

[108] JONES, E., BROWNING, B., DIAS, M., ARGALL, B., VELOSO, M., AND STENTZ, A. Dynamically formed heterogeneous robot teams performing tightly-coordinated tasks. In *Proceedings 2006 IEEE International Conference on Robotics and Automation, 2006. ICRA 2006.* (Orlando, FL, USA, 2006), IEEE, pp. 570–575.

[109] JUNG, H., AND SONG, Y.-E. Robotic remote control based on human motion via virtual collaboration system: A survey. *Journal of Advanced Mechanical Design, Systems, and Manufacturing 12*, 7 (2018), JAMDSM0126–JAMDSM0126.

[110] KABER, D. B., AND ENDSLEY, M. R. Out-of-the-loop performance problems and the use of intermediate levels of automation for improved control system functioning and safety. *Process Safety Progress 16*, 3 (1997), 126–131.

[111] KABER, D. B., AND ENDSLEY, M. R. Team situation awareness for process control safety and performance. *Process Safety Progress 17*, 1 (1998), 43–48.

[112] KALPAGAM GANESAN, R., RATHORE, Y. K., ROSS, H. M., AND BEN AMOR, H. Better Teaming Through Visual Cues: How Projecting Imagery in a Workspace Can Improve Human-Robot Collaboration. *IEEE Robotics & Automation Magazine 25*, 2 (June 2018), 59–71.

[113] KAPELLMANN-ZAFRA, G., SALOMONS, N., KOLLING, A., AND GRO\S S, R. Human-Robot Swarm Interaction with Limited Situational Awareness. In *International Conference on Swarm Intelligence* (2016), Springer, pp. 125–136.

[114] KESKINPALA, H. K., AND ADAMS, J. A. Objective data analysis for a pda-based human robotic interface. In *2004 IEEE International Conference on Systems, Man and Cybernetics (IEEE Cat. No. 04CH37583)* (2004), vol. 3, IEEE, pp. 2809–2814.

[115] KHEDDAR, A., CHELLALI, R., AND COIFFET, P. Virtual environment–assisted teleoperation, 2014.

[116] KIM, J., OH, S., AND KIM, D. Implementation of a work distribution function for tele-operation under multi-user and multi-robot environments. 4.

[117] KIM, J., YUN, S., YOO, J., AND KIM, D. Implementation of N:1/1:N work distribution function for tele-operation under multi-user and multi-robot environments. In *2013 10th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI)* (Jeju, Korea (South), Oct. 2013), IEEE, pp. 328–330.

[118] KIM, T., AND HINDS, P. Who should i blame? effects of autonomy and transparency on attributions in human-robot interaction. In *ROMAN 2006-The 15th IEEE International Symposium on Robot and Human Interactive Communication* (2006), IEEE, pp. 80–85.

[119] KLOW, J., PROBY, J., RUEBEN, M., SOWELL, R. T., GRIMM, C. M., AND SMART, W. D. Privacy, Utility, and Cognitive Load in Remote Presence Systems. In *Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-Robot Interaction* (Vienna Austria, Mar. 2017), ACM, pp. 167–168.

[120] KLOW, J., PROBY, J., RUEBEN, M., SOWELL, R. T., GRIMM, C. M., AND SMART, W. D. Privacy, Utility, and Cognitive Load in Remote Presence Systems. In *Social Robotics*, M. A. Salichs, S. S. Ge, E. I. Barakova, J.-J. Cabibihan, A. R. Wagner, A. Castro-González, and H. He, Eds., vol. 11876. Springer International Publishing, Cham, 2019, pp. 730–739. Series Title: Lecture Notes in Computer Science.

[121] KNIGHT, H., THIELSTROM, R., AND SIMMONS, R. Expressive path shape (swagger): Simple features that illustrate a robot's attitude toward its goal in real time. In *Intelligent Robots and Systems (IROS), 2016 IEEE/RSJ International Conference on* (2016), IEEE, pp. 1475–1482.

[122] KOLLING, A., SYCARA, K., NUNNALLY, S., AND LEWIS, M. Human Swarm Interaction: An Experimental Study of Two Types of Interaction with Foraging Swarms. *Journal of Human-Robot Interaction 2*, 2 (June 2013).

[123] KOLLING, A., WALKER, P., CHAKRABORTY, N., SYCARA, K., AND LEWIS, M. Human Interaction With Robot Swarms: A Survey. *IEEE Transactions on Human-Machine Systems 46*, 1 (Feb. 2016), 9–26.

[124] LAGER, M., TOPP, E. A., AND MALEC, J. Remote Supervision of an Unmanned Surface Vessel - A Comparison of Interfaces. In *2019 14th ACM/IEEE International*

Conference on Human-Robot Interaction (HRI) (Daegu, Korea (South), Mar. 2019), IEEE, pp. 546–547.

[125] LAKHMANI, S., ABICH, J., BARBER, D., AND CHEN, J. A Proposed Approach for Determining the Influence of Multimodal Robot-of-Human Transparency Information on Human-Agent Teams. In *Foundations of Augmented Cognition: Neuroergonomics and Operational Neuroscience*, D. D. Schmorrow and C. M. Fidopiastis, Eds., vol. 9744. Springer International Publishing, Cham, 2016, pp. 296–307.

[126] LAKHMANI, S. G., WRIGHT, J. L., SCHWARTZ, M. R., AND BARBER, D. Exploring the Effect of Communication Patterns and Transparency on Performance in a Human-Robot Team. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting 63*, 1 (Nov. 2019), 160–164.

[127] LANE, J. C., CARIGNAN, C. R., SULLIVAN, B. R., AKIN, D. L., HUNT, T., AND COHEN, R. Effects of time delay on telerobotic control of neutral buoyancy vehicles. In *Proceedings 2002 IEEE International Conference on Robotics and Automation (Cat. No. 02CH37292)* (2002), vol. 3, IEEE, pp. 2874–2879.

[128] LE GOC, M., KIM, L. H., PARSAEI, A., FEKETE, J.-D., DRAGICEVIC, P., AND FOLLMER, S. Zooids: Building Blocks for Swarm User Interfaces. In *Proceedings of the 29th Annual Symposium on User Interface Software and Technology - UIST '16* (Tokyo, Japan, 2016), ACM Press, pp. 97–109.

[129] LEE, D., FRANCHI, A., SON, H. I., HA, C., BULTHOFF, H. H., AND GIORDANO, P. R. Semiautonomous Haptic Teleoperation Control Architecture of Multiple Unmanned Aerial Vehicles. *IEEE/ASME Transactions on Mechatronics 18*, 4 (Aug. 2013), 1334–1345.

[130] LEE, J. D. Review of a pivotal human factors article:"humans and automation: use, misuse, disuse, abuse". *Human Factors 50*, 3 (2008), 404–410.

[131] LEE, J. D., AND SEE, K. A. Trust in automation: Designing for appropriate reliance. *Human factors 46*, 1 (2004), 50–80.

[132] LEE, P.-J., WANG, H., CHIEN, S.-Y., LEWIS, M., SCERRI, P., VELAGAPUDI, P., SYCARA, K., AND KANE, B. Teams for Teams Performance in Multi-Human/Multi-Robot Teams. *th ANNUAL MEETING* (2010), 5.

[133] LEE, P. U. Understanding human-human collaboration to guide human-computer interaction design in air traffic control. In *2005 IEEE International Conference on Systems, Man and Cybernetics* (2005), vol. 2, IEEE, pp. 1598–1603.

[134] LEE, S., LUCAS, N. P., ELLIS, R. D., AND PANDYA, A. Development and human factors analysis of an augmented reality interface for multi-robot tele-operation and control. p. 83870N.

[135] LEWIS, B., AND SUKTHANKAR, G. Two hands are better than one: Assisting users with multi-robot manipulation tasks. In *2011 IEEE/RSJ International Conference on Intelligent Robots and Systems* (San Francisco, CA, Sept. 2011), IEEE, pp. 2590–2595.

[136] LEWIS, M. Human interaction with multiple remote robots. *Reviews of Human Factors and Ergonomics 9*, 1 (2013), 131–174.

[137] LEWIS, M., AND SYCARA, K. Effects of automation on situation awareness in controlling robot teams. 7.

[138] LEWIS, M., WANG, H., CHIEN, S. Y., VELAGAPUDI, P., SCERRI, P., AND SYCARA, K. Choosing autonomy modes for multirobot search. *Human Factors 52*, 2 (2010), 225–233.

[139] LEWIS, M., WANG, H., SHIH-YI CHIEN, SCERRI, P., VELAGAPUDI, P., SYCARA, K., AND KANE, B. Teams organization and performance in multi-human/multi-robot teams. In *2010 IEEE International Conference on Systems, Man and Cybernetics* (Istanbul, Turkey, Oct. 2010), IEEE, pp. 1617–1623.

[140] LEWIS, M., WANG, J., AND SCERRI, P. Teamwork coordination for realistically complex multi robot systems. In *NATO Symposium on Human Factors of Uninhabited Military Vehicles as Force Multipliers* (2006), pp. 1–12.

[141] LI, H., ZHANG, L., AND KAWASHIMA, K. Operator dynamics for stability condition in haptic and teleoperation system: A survey. *The International Journal of Medical Robotics and Computer Assisted Surgery 14*, 2 (Apr. 2018), e1881.

[142] LICHIARDOPOL, S. A Survey on Teleoperation. 34.

[143] LIKERT, R. A technique for the measurement of attitudes. *Arch Psych 140* (1932), 55.

[144] LIU, H., ZHANG, Y., SI, W., XIE, X., ZHU, Y., AND ZHU, S.-C. Interactive Robot Knowledge Patching Using Augmented Reality. In *2018 IEEE International Conference on Robotics and Automation (ICRA)* (Brisbane, QLD, May 2018), IEEE, pp. 1947–1954.

[145] LIU, P., GLAS, D. F., KANDA, T., AND ISHIGURO, H. Data-driven hri: Learning social behaviors by example from human–human interaction. *IEEE Transactions on Robotics 32*, 4 (2016), 988–1008.

[146] LIU, Z., WU, M., CAO, W., CHEN, L., XU, J., ZHANG, R., ZHOU, M., AND MAO, J. A facial expression emotion recognition based human-robot interaction system.

[147] LUNGHI, G., MARIN, R., DI CASTRO, M., MASI, A., AND SANZ, P. J. Multimodal Human-Robot Interface for Accessible Remote Robotic Interventions in Hazardous Environments. *IEEE Access 7* (2019), 127290–127319.

[148] LYONS, J. B. Being transparent about transparency: A model for human-robot interaction. In *2013 AAAI Spring Symposium Series* (2013).

[149] MA, L., YAN, J., ZHAO, J., CHEN, Z., AND CAI, H. Teleoperation System of Internet-Based Multi-Operator Multi-Mobile-Manipulator. In *2010 International Conference on Electrical and Control Engineering* (Wuhan, China, June 2010), IEEE, pp. 2236–2240.

[150] MACKENZIE, I. S., AND WARE, C. Lag as a determinant of human performance in interactive systems. In *Proceedings of the INTERACT'93 and CHI'93 conference on Human factors in computing systems* (1993), pp. 488–493.

[151] MADHAVAN, P., AND WIEGMANN, D. A. Similarities and differences between human–human and human–automation trust: an integrative review. *Theoretical Issues in Ergonomics Science 8*, 4 (2007), 277–301.

[152] MALIK, A. A., AND BILBERG, A. Developing a reference model for human–robot interaction. *International Journal on Interactive Design and Manufacturing (IJIDeM)* (June 2019).

[153] MALVANKAR-MEHTA, M. S., AND MEHTA, S. S. Optimal task allocation in multi-human multi-robot interaction. *Optimization Letters 9*, 8 (Dec. 2015), 1787–1803.

[154] MANSOUR, C., SHAMMAS, E., ELHAJJ, I. H., AND ASMAR, D. Dynamic bandwidth management for teleoperation of collaborative robots. In *2012 IEEE International Conference on Robotics and Biomimetics (ROBIO)* (Guangzhou, China, Dec. 2012), IEEE, pp. 1861–1866.

[155] MASSIMINO, M. J., AND SHERIDAN, T. B. Teleoperator performance with varying force and visual feedback. *Human factors 36*, 1 (1994), 145–157.

[156] MATTHEWS, G., LIN, J., PANGANIBAN, A. R., AND LONG, M. D. Individual Differences in Trust in Autonomous Robots: Implications for Transparency. *IEEE Transactions on Human-Machine Systems* (2019), 1–11.

[157] MAVRIDIS, N. A review of verbal and non-verbal human–robot interactive communication. *Robotics and Autonomous Systems 63* (2015), 22–35.

[158] MCBRIDE, S. E., ROGERS, W. A., AND FISK, A. D. Understanding the effect of workload on automation use for younger and older adults. *Human factors 53*, 6 (2011), 672–686.

[159] MERCADO, J. E., RUPP, M. A., CHEN, J. Y. C., BARNES, M. J., BARBER, D., AND PROCCI, K. Intelligent Agent Transparency in Human–Agent Teaming for Multi-UxV Management. *Human Factors: The Journal of the Human Factors and Ergonomics Society 58*, 3 (May 2016), 401–415.

[160] MILLER, G. A. The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological review 63*, 2 (1956), 81.

[161] MORTENSEN, D. H. User aware technology: From inter-human awareness to technology-user awareness. In *IFIP Conference on Human-Computer Interaction* (2009), Springer, pp. 884–887.

[162] MURPHY, R. R. A decade of rescue robots. In *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems* (2012), IEEE, pp. 5448–5449.

[163] MURPHY, R. R. *Disaster robotics*. MIT press, 2014.

[164] MURPHY, R. R., AND SCHRECKENGHOST, D. Survey of metrics for human-robot interaction. In *2013 8th ACM/IEEE International Conference on Human-Robot Interaction (HRI)* (Tokyo, Japan, Mar. 2013), IEEE, pp. 197–198.

[165] MURPHY, R. R., TADOKORO, S., AND KLEINER, A. Disaster Robotics. In *Springer Handbook of Robotics*. Springer, 2016, pp. 1577–1604.

[166] MUSIC, S., SALVIETTI, G., DOHMANN, P. B. G., CHINELLO, F., PRATTICHIZZO, D., AND HIRCHE, S. Human–Robot Team Interaction Through Wearable Haptics for Cooperative Manipulation. *IEEE Transactions on Haptics 12*, 3 (July 2019), 350–362.

[167] NAGAVALLI, S., CHANDARANA, M., SYCARA, K., AND LEWIS, M. Multi-operator gesture control of robotic swarms using wearable devices. In *Proceedings of the Tenth International Conference on Advances in Computer-Human Interactions* (2017), IARIA.

[168] NAGI, J., GIUSTI, A., DI CARO, G. A., AND GAMBARDELLA, L. M. HRI in the sky: controlling UAVs using face poses and hand gestures. In *Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction - HRI '14* (Bielefeld, Germany, 2014), ACM Press, pp. 252–253.

[169] NAGI, J., GIUSTI, A., GAMBARDELLA, L. M., AND DI CARO, G. A. Human-swarm interaction using spatial gestures. In *2014 IEEE/RSJ International Conference on Intelligent Robots and Systems* (Chicago, IL, USA, Sept. 2014), IEEE, pp. 3834–3841.

[170] NAGI, J., GIUSTI, A., NAGI, F., GAMBARDELLA, L. M., AND DI CARO, G. A. Online feature extraction for the incremental learning of gestures in human-swarm interaction. In *Robotics and Automation (ICRA), 2014 IEEE International Conference on* (2014), IEEE, pp. 3331–3338.

[171] NAK YOUNG CHONG, KOTOKU, T., OHBA, K., KOMORIYA, K., MATSUHIRA, N., AND TANIE, K. Remote coordinated controls in multiple telerobot cooperation. In *Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation. Symposia Proceedings (Cat. No.00CH37065)* (San Francisco, CA, USA, 2000), vol. 4, IEEE, pp. 3138–3143.

[172] NIELSEN, C. W., AND GOODRICH, M. A. Comparing the usefulness of video and map information in navigation tasks. In *Proceedings of the 1st ACM SIGCHI/SIGART conference on Human-robot interaction* (2006), pp. 95–101.

[173] NIKOLA, T. Method of and apparatus for controlling mechanism of moving vessels or vehicles, Nov. 8 1898. US Patent 613,809.

[174] NORMAN, D. *The Design of Everyday Things*. Basic Books, 2013.

[175] OH, J.-K., JANG, G., OH, S., LEE, J. H., YI, B.-J., MOON, Y. S., LEE, J. S., AND CHOI, Y. Bridge inspection robot system with machine vision. *Automation in Construction 18*, 7 (2009), 929–941.

[176] ONG, K. S., HSU, Y. H., AND FU, L. C. Sensor fusion based human detection and tracking system for human-robot interaction. In *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems* (Vilamoura-Algarve, Portugal, Oct. 2012), IEEE, pp. 4835–4840.

[177] OSOSKY, S., SANDERS, T., JENTSCH, F., HANCOCK, P., AND CHEN, J. Y. Determinants of system transparency and its influence on trust in and reliance on unmanned robotic systems. In *Unmanned Systems Technology XVI* (2014), vol. 9084, International Society for Optics and Photonics, p. 90840E.

[178] ÖZ"UR, A., LEMAIGNAN, S., JOHAL, W., BELTRAN, M., BRIOD, M., PEREYRE, L., MONDADA, F., AND DILLENBOURG, P. Cellulo: Versatile Handheld Robots for Education. In *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction - HRI '17* (Vienna, Austria, 2017), ACM Press, pp. 119–127.

[179] PANGANIBAN, A. R., MATTHEWS, G., AND LONG, M. D. Transparency in Autonomous Teammates: Intention to Support as Teaming Information. *Journal of Cognitive Engineering and Decision Making* (Nov. 2019), 155534341988156.

[180] PARASURAMAN, R., AND RILEY, V. Humans and automation: Use, misuse, disuse, abuse. *Human factors 39*, 2 (1997), 230–253.

[181] PARUNAK, H. V. D. A survey of environments and mechanisms for human-human stigmergy. In *International workshop on environments for multi-agent systems* (2005), Springer, pp. 163–186.

[182] PATEL, J., XU, Y., AND PINCIROLI, C. Mixed-granularity human-swarm interaction. In *2019 International Conference on Robotics and Automation (ICRA)* (2019), pp. 1059–1065.

[183] PATEL, J., XU, Y., AND PINCIROLI, C. Mixed-Granularity Human-Swarm Interaction. In *2019 IEEE International Conference on Robotics and Automation (ICRA)* (Montreal, Canada, Jan. 2019), IEEE. arXiv: 1901.08522.

[184] PATEL, T. M., SHAH, S. C., AND PANCHOLY, S. B. Long Distance Tele-Robotic-Assisted Percutaneous Coronary Intervention: A Report of First-in-Human Experience. *EClinicalMedicine 14* (Sept. 2019), 53–58.

[185] PETERS, C., CASTELLANO, G., AND DE FREITAS, S. An exploration of user engagement in hci. In *Proceedings of the International Workshop on Affective-Aware Virtual Agents and Social Robots* (2009), pp. 1–3.

[186] PINCIROLI, C., TRIANNI, V., O'GRADY, R., PINI, G., BRUTSCHY, A., BRAMBILLA, M., MATHEWS, N., FERRANTE, E., DI CARO, G., DUCATELLE, F., BIRATTARI, M., GAMBARDELLA, L. M., AND DORIGO, M. ARGoS: a modular, parallel, multi-engine simulator for multi-robot systems. *Swarm Intelligence 6*, 4 (2012), 271–295.

[187] PODEVIJN, G., O'GRADY, R., NASHED, Y. S. G., AND DORIGO, M. Gesturing at Subswarms: Towards Direct Human Control of Robot Swarms. In *Towards Autonomous Robotic Systems*, A. Natraj, S. Cameron, C. Melhuish, and M. Witkowski, Eds., vol. 8069. Springer Berlin Heidelberg, Berlin, Heidelberg, 2014, pp. 390–403.

[188] POKAM, R., DEBERNARD, S., CHAUVIN, C., AND LANGLOIS, S. Principles of transparency for autonomous vehicles: first results of an experiment with an augmented reality human–machine interface. *Cognition, Technology & Work 21*, 4 (Nov. 2019), 643–656.

[189] RAKITA, D., MUTLU, B., AND GLEICHER, M. Remote Telemanipulation with Adapting Viewpoints in Visually Complex Environments. In *Robotics: Science and Systems XV* (June 2019), Robotics: Science and Systems Foundation.

[190] RASTOGI, A. Design of an interface for teleoperation in unstructured environments using augmented reality displays.

[191] REGENBRECHT, J., TAVAKKOLI, A., AND LOFFREDO, D. An Intuitive Human Interface for Remote Operation of Robotic Agents in Immersive Virtual Reality Environments. 3.

[192] Ricks, B., Nielsen, C. W., and Goodrich, M. A. Ecological displays for robot interaction: A new perspective. In *2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)(IEEE Cat. No. 04CH37566)* (2004), vol. 3, IEEE, pp. 2855–2860.

[193] Riley, J. M., and Endsley, M. R. Situation awareness in hri with collaborating remotely piloted vehicles. In *proceedings of the Human Factors and Ergonomics Society Annual Meeting* (2005), vol. 49, SAGE Publications Sage CA: Los Angeles, CA, pp. 407–411.

[194] Roldan, J. J., Pena-Tapia, E., Garcia-Aunon, P., Del Cerro, J., and Barrientos, A. Bringing Adaptive and Immersive Interfaces to Real-World Multi-Robot Scenarios: Application to Surveillance and Intervention in Infrastructures. *IEEE Access 7* (2019), 86319–86335.

[195] Rotsidis, A., Theodorou, A., Bryson, J. J., and Wortham, R. H. Improving Robot Transparency: An Investigation With Mobile Augmented Reality. In *2019 28th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)* (New Delhi, India, Oct. 2019), IEEE, pp. 1–8.

[196] Roundtree, K. A., Goodrich, M. A., and Adams, J. A. Transparency: Transitioning From Human–Machine Systems to Human-Swarm Systems. *Journal of Cognitive Engineering and Decision Making* (Apr. 2019), 155534341984277.

[197] Rubio, R. F. Mining: the challenge knocks on our door. *Mine Water and the Environment 31*, 1 (2012), 69–73.

[198] Sanders, T. L., Wixon, T., Schafer, K. E., Chen, J. Y. C., and Hancock, P. A. The influence of modality and transparency on trust in human-robot interaction. In *2014 IEEE International Inter-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA)* (San Antonio, TX, USA, Mar. 2014), IEEE, pp. 156–159.

[199] Sartorato, F., Przybylowski, L., and Sarko, D. K. Improving therapeutic outcomes in autism spectrum disorders: Enhancing social communication and sensory processing through the use of interactive robots. *Journal of psychiatric research 90* (2017), 1–11.

[200] SAUNDERSON, S., AND NEJAT, G. How robots influence humans: A survey of nonverbal communication in social human–robot interaction. *International Journal of Social Robotics 11*, 4 (2019), 575–608.

[201] SCHAEFER, K. E. Measuring trust in human robot interactions: Development of the "trust perception scale-hri". In *Robust Intelligence and Trust in Autonomous Systems*. Springer, 2016, pp. 191–218.

[202] SCHAUSS, T., GROTEN, R., PEER, A., AND BUSS, M. Evaluation of a Coordinating Controller for Improved Task Performance in Multi-user Teleoperation. In *Haptics: Generating and Perceiving Tangible Sensations*, D. Hutchison, T. Kanade, J. Kittler, J. M. Kleinberg, F. Mattern, J. C. Mitchell, M. Naor, O. Nierstrasz, C. Pandu Rangan, B. Steffen, M. Sudan, D. Terzopoulos, D. Tygar, M. Y. Vardi, G. Weikum, A. M. L. Kappers, J. B. F. van Erp, W. M. Bergmann Tiest, and F. C. T. van der Helm, Eds., vol. 6191. Springer Berlin Heidelberg, Berlin, Heidelberg, 2010, pp. 240–247. Series Title: Lecture Notes in Computer Science.

[203] SCHOLTZ, J. Theory and evaluation of human robot interactions. In *36th Annual Hawaii International Conference on System Sciences, 2003. Proceedings of the* (Big Island, HI, USA, 2003), IEEE, p. 10 pp.

[204] SCHOLTZ, J., YOUNG, J., DRURY, J. L., AND YANCO, H. A. Evaluation of human-robot interaction awareness in search and rescue. In *IEEE International Conference on Robotics and Automation, 2004. Proceedings. ICRA'04. 2004* (2004), vol. 3, IEEE, pp. 2327–2332.

[205] SELCON, S., TAYLOR, R., AND KORITSAS, E. Workload or situational awareness?: Tlx vs. sart for aerospace systems design evaluation. In *Proceedings of the Human Factors Society Annual Meeting* (1991), vol. 35, SAGE Publications Sage CA: Los Angeles, CA, pp. 62–66.

[206] SELKOWITZ, A., LAKHMANI, S., CHEN, J. Y., AND BOYCE, M. The Effects of Agent Transparency on Human Interaction with an Autonomous Robotic Agent. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting 59*, 1 (Sept. 2015), 806–810.

[207] SELKOWITZ, A. R., LARIOS, C. A., LAKHMANI, S. G., AND CHEN, J. Y. Displaying Information to Support Transparency for Autonomous Platforms. In *Advances*

in Human Factors in Robots and Unmanned Systems, P. Savage-Knepshield and J. Chen, Eds., vol. 499. Springer International Publishing, Cham, 2017, pp. 161–173.

[208] SETTER, T., FOURAKER, A., KAWASHIMA, H., AND EGERSTEDT, M. Haptic Interactions With Multi-Robot Swarms Using Manipulability. *Journal of Human-Robot Interaction 4*, 1 (Jan. 2015), 60.

[209] SHAHZAD, N., CHAWLA, T., AND GALA, T. Telesurgery prospects in delivering healthcare in remote areas. 4.

[210] SHEPARDSON, D. New documents show uber self-driving cars were involved in 37 crashes before a fatal incident temporarily shut the program down last years, November 2019. [Online; posted 6-Nov-2019, 8:57AM.

[211] SHERIDAN, T. B. *Humans and automation: System design and research issues.* Human Factors and Ergonomics Society, 2002.

[212] SHERIDAN, T. B., AND FERRELL, W. R. Remote manipulative control with transmission delay. *IEEE Transactions on Human Factors in Electronics*, 1 (1963), 25–29.

[213] SIROUSPOUR, S., AND SETOODEH, P. Multi-operator/multi-robot teleoperation: an adaptive nonlinear control approach. In *2005 IEEE/RSJ International Conference on Intelligent Robots and Systems* (2005), IEEE, pp. 1576–1581.

[214] STEFANOV, N., PEER, A., AND BUSS, M. Role determination in human-human interaction. In *World Haptics 2009-Third Joint EuroHaptics conference and Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems* (2009), IEEE, pp. 51–56.

[215] STEINFELD, A., FONG, T., KABER, D., LEWIS, M., SCHOLTZ, J., SCHULTZ, A., AND GOODRICH, M. Common metrics for human-robot interaction. In *Proceeding of the 1st ACM SIGCHI/SIGART conference on Human-robot interaction - HRI '06* (Salt Lake City, Utah, USA, 2006), ACM Press, p. 33.

[216] STOWERS, K., KASDAGLIS, N., NEWTON, O., LAKHMANI, S., WOHLEBER, R., AND CHEN, J. Intelligent Agent Transparency: The Design and Evaluation of an Interface to Facilitate Human and Intelligent Agent Collaboration. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting 60*, 1 (Sept. 2016), 1706–1710.

[217] SUN, R., ET AL. *Cognition and multi-agent interaction: From cognitive modeling to social simulation*. Cambridge University Press, 2006.

[218] TAYLOR, R. M. Situational awareness rating technique (sart): The development of a tool for aircrew systems design. In *Situational awareness*. Routledge, 1990, pp. 111–128.

[219] THEODOROU, A., WORTHAM, R. H., AND BRYSON, J. J. Why is my robot behaving like that? Designing transparency for real time inspection of autonomous robots. 4.

[220] TOMASELLO, M. *Origins of human communication*. MIT press, 2010.

[221] TSAROUCHI, P., MICHALOS, G., MAKRIS, S., ATHANASATOS, T., DIMOULAS, K., AND CHRYSSOLOURIS, G. On a human–robot workplace design and task allocation system. *International Journal of Computer Integrated Manufacturing 30*, 12 (Dec. 2017), 1272–1279.

[222] TSENG, S.-H., HSU, Y.-H., CHIANG, Y.-S., WU, T.-Y., AND FU, L.-C. Multi-human spatial social pattern understanding for a multi-modal robot through nonverbal social signals. In *The 23rd IEEE International Symposium on Robot and Human Interactive Communication* (Edinburgh, UK, Aug. 2014), IEEE, pp. 531–536.

[223] TULLI, S., CORREIA, F., MASCARENHAS, S., MELO, F. S., AND PAIVA, A. Effects of Agents' Transparency on Teamwork? 16.

[224] UGGIRALA, A., GRAMOPADHYE, A. K., MELLOY, B. J., AND TOLER, J. E. Measurement of trust in complex and dynamic systems using a quantitative approach. *International Journal of Industrial Ergonomics 34*, 3 (2004), 175–186.

[225] VARKONYI, T. A., RUDAS, I. J., PAUSITS, P., AND HAIDEGGER, T. Survey on the control of time delay teleoperation systems. In *IEEE 18th International Conference on Intelligent Engineering Systems INES 2014* (Tihany, Hungary, July 2014), IEEE, pp. 89–94.

[226] VELTE, T., VELTE, A., AND ELSENPETER, R. *Cloud computing, a practical approach*. McGraw-Hill, Inc., 2009.

[227] VILLANI, V., CAPELLI, B., SECCHI, C., FANTUZZI, C., AND SABATTINI, L. Humans interacting with multi-robot systems: a natural affect-based approach. *Autonomous Robots 44*, 3-4 (Mar. 2020), 601–616.

[228] VINCIARELLI, A., ESPOSITO, A., ANDRÉ, E., BONIN, F., CHETOUANI, M., COHN, J. F., CRISTANI, M., FUHRMANN, F., GILMARTIN, E., HAMMAL, Z., ET AL. Open challenges in modelling, analysis and synthesis of human behaviour in human–human and human–machine interactions. *Cognitive Computation 7*, 4 (2015), 397–413.

[229] WANG, Y., HUMPHREY, L. R., LIAO, Z., AND ZHENG, H. Trust-based Multi-Robot Symbolic Motion Planning with a Human-in-the-Loop. *ACM Transactions on Interactive Intelligent Systems 8*, 4 (Nov. 2018), 1–33. arXiv: 1808.05120.

[230] WARREN, J., RIXNER, S., GREINER, J., AND WONG, S. Facilitating human interaction in an online programming course. In *Proceedings of the 45th ACM technical symposium on Computer science education* (2014), pp. 665–670.

[231] WATSON, B., WALKER, N., RIBARSKY, W., AND SPAULDING, V. Effects of variation in system responsiveness on user performance in virtual environments. *Human Factors 40*, 3 (1998), 403–414.

[232] WEINBERG, G., BLOSSER, B., MALLIKARJUNA, T., AND RAMAN, A. The Creation of a Multi-Human, Multi-Robot Interactive Jam Session. 4.

[233] WEISS, A., MIRNIG, N., BUCHNER, R., FÖRSTER, F., AND TSCHELIGI, M. Transferring human-human interaction studies to hri scenarios in public space. In *IFIP Conference on Human-Computer Interaction* (2011), Springer, pp. 230–247.

[234] WELBURN, E., WRIGHT, T., MARSH, C., LIM, S., GUPTA, A., CROWTHER, W., AND WATSON, S. A Mixed Reality Approach to Robotic Inspection of Remote Environments. In *Embedded Inteligence: Enabling & Supporting RAS Technologies* (Jan. 2019), UK-RAS Network, pp. 72–74.

[235] WOHLEBER, R. W., STOWERS, K., CHEN, J. Y., AND BARNES, M. Effects of agent transparency and communication framing on human-agent teaming. In *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)* (Banff, AB, Oct. 2017), IEEE, pp. 3427–3432.

[236] WOJTON, H. M., PORTER, D., T. LANE, S., BIEBER, C., AND MADHAVAN, P. Initial validation of the trust of automated systems test (TOAST). *The Journal of Social Psychology* (Apr. 2020), 1–16.

[237] WRIGHT, J. L. Transparency in Human-agent Teaming and its Effect on Automation-induced Complacency. *Procedia Manufacturing 3* (2015), 968–973.

[238] WRIGHT, J. L., CHEN, J. Y., BARNES, M. J., AND BOYCE, M. W. The Effects of Information Level on Human-Agent Interaction for Route Planning. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting 59*, 1 (Sept. 2015), 811–815.

[239] WRIGHT, J. L., CHEN, J. Y., BARNES, M. J., AND HANCOCK, P. A. Agent reasoning transparency: The influence of information level on automation induced complacency. Tech. rep., US Army Research Laboratory Aberdeen Proving Ground United States, 2017.

[240] WRIGHT, J. L., CHEN, J. Y. C., AND LAKHMANI, S. G. Agent Transparency and Reliability in Human–Robot Interaction: The Influence on User Confidence and Perceived Reliability. *IEEE Transactions on Human-Machine Systems* (2019), 1–10.

[241] XIA, F., HSU, C.-H., LIU, X., LIU, H., DING, F., AND ZHANG, W. The power of smartphones. *Multimedia Systems 21*, 1 (2015), 87–101.

[242] YANCO, H., AND DRURY, J. Classifying human-robot interaction: an updated taxonomy. In *2004 IEEE International Conference on Systems, Man and Cybernetics (IEEE Cat. No.04CH37583)* (The Hague, Netherlands, 2004), vol. 3, IEEE, pp. 2841–2846.

[243] YOU, S., AND ROBERT, L. Teaming up with Robots: An IMOI (Inputs-Mediators-Outputs-Inputs) Framework of Human-Robot Teamwork. 7.

[244] YOU, S., AND ROBERT JR, L. Curiosity vs. control: Impacts of training on performance of teams working with robots. In *Proceedings of the 19th ACM Conference on Computer Supported Cooperative Work and Social Computing Companion* (2016), ACM, pp. 449–452.

[245] You, S., and Robert Jr., L. E. Curiosity vs. Control: Impacts of Training on Performance of Teams Working with Robots. In *Proceedings of the 19th ACM Conference on Computer Supported Cooperative Work and Social Computing Companion - CSCW '16 Companion* (San Francisco, California, USA, 2016), ACM Press, pp. 449–452.

[246] Yussiff, A.-L., Yong, S.-P., and Baharudin, B. B. Parallel kalman filter-based multi-human tracking in surveillance video. In *2014 International Conference on Computer and Information Sciences (ICCOINS)* (2014), IEEE, pp. 1–6.

[247] ZAPPER, G. How robots became essential workers.

[248] Zhang, L., and Vaughan, R. Optimal robot selection by gaze direction in multi-human multi-robot interaction. In *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (Daejeon, South Korea, Oct. 2016), IEEE, pp. 5077–5083.

[249] Zhu, Y., Aoyama, T., and Hasegawa, Y. Enhancing the Transparency by Onomatopoeia for Passivity-Based Time-Delayed Teleoperation. *IEEE Robotics and Automation Letters 5*, 2 (Apr. 2020), 2981–2986.