Abstract—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 previous work, we studied how this issue can be tackled by interacting with the robots in two modalities — environment-oriented and robot-oriented. In this paper, we study how this concept can be applied to the case in which multiple human operators perform supervisory control on a multi-robot system. While the presence of extra operators suggests that more complex tasks could be accomplished, little research exists on how this could be achieved efficiently. In particular, one challenge arises — the out-of-the-loop performance problem caused by a lack of engagement in the task, awareness of its state, and trust in the system and in the other operators. Through a user study involving 28 human operators and 8 real robots, we study how the concept of mixed granularity in multi-human multi-robot interaction affects user engagement, awareness, and trust while balancing the workload between multiple operators.

I. INTRODUCTION

Multi-robot systems will assist humans in accomplishing complex tasks [1], including home maintenance [2], mining [3], bridge inspection [4], disaster recovery [5], [6], and colonizing the cosmos [7]. In all these applications, robot autonomy is a necessary but not sufficient condition. Along with autonomy, an equally important component of these systems is the ability for humans to supervise and affect the behavior of the robots over the duration of the mission [8].

By their very nature, multi-robot systems are complex systems composed of many interacting parts. As such, these systems often exceed the span of apprehension of any individual human, which is typically limited to 7(±2) entities [9], [10]. This limits the performance of the operators, which is typically measured in terms of workload, situational awareness, and trust in the system [11], [12], [13]. A natural approach to improving human performance is to relieve the burden of individual operators by conceiving of supervisory control schemes in which multiple operators cooperate.

However, with multiple humans in the system, additional challenges arise, such as coping with ineffective group dynamics [14], unbalanced workload [15], [13], and inhomogeneous awareness [16], [17], [18]. 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 [19], [20].

Little research exists on these topics in the context of multi-robot systems. In this paper, we extend our previous work on mixed-granularity control of multi-robot systems to study how our approach affects the performance of multiple human operators. In previous work, we showed that allowing an operator to control two levels of granularity—the task goal (by modifying the environment) and the individual robots—improves the performance of the human operator [21]. In this study, we explore how this modality of interaction affects the performance of multiple cooperating operators.

This paper offers two main contributions:

- From the technological point of view, we created the first mixed-granularity interface for multi-human-multi-robot interaction. Our interface is based on a networked augmented 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, we assessed the validity of our approach through a user study of our 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 paper is organized as follows. In Sec. II we discuss related work on human-robot interfaces. In Sec. III we present our system and its design. In Sec. IV we detail our user study, followed by a discussion of the results in Sec. V. We conclude the paper in Sec. VI.

II. BACKGROUND

According to Endsley [11], granularity of control is a key aspect affecting the OOTL phenomenon. Low-level control includes robot selection and manipulation [22], [23], [24], [25], [26], [27], [28], [29], [30], while high-level control comprises of global goal manipulation by defining navigation goals [31], [32], [33], [34], team organization [35], [36], or allocating tasks [37]. Limiting control to one type of granularity creates a fundamental tradeoff [11]. 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 [38], [39], [40], [41], [42], [43] and human tracking [44], [45], [46], [47], [48]. Other works focus on how to coordinate teams of humans and robots [49], [50], [51], [52], [53], [54], [35]. In supervisory control, past work focused on investigating the influence of autonomy and resource sharing on the task performance [24], [22]. Researchers also investigated the effects of curiosity and training on increasing task performance [23]. However, to the best of our knowledge, there has not been any study on the out-of-the-loop performance problem in the context of multi-robot systems.

III. The Networked Augmented Reality App

A. System Overview

The system is comprised of four components (see Fig. 1):

1) A distributed augmented 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 [55], a multi-robot simulator acting as a middleware responsible for channeling data to the robots.

The operation of the system 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 AR app users and ARGoS. The other AR 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.

B. User Interface

The interaction between operators and robots occurs through an Augmented Reality (AR) application installed on handheld devices, such as smartphones or tablets. The app integrates Vuforia [56], a software development kit for AR applications, and the Unity Game Engine [57]. 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 a some or all of the robots with a one-finger swipe. Fig. 2 shows the screenshot of the AR 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, toggling obstacle avoidance and toggling visibility and detection of objects and robots. The bottom-right corner houses the button for creating virtual objects dynamically.

C. Interaction Modes

Object Manipulation. The app overlays a virtual object over the real object. The operator can manipulate this virtual object to define its desired position. The app allows the operator to move multiple objects through this gesture, and the respective team of robots will transport the objects in
parallel when enough robots are available. If the available robots are not sufficient for a task, the app queues the request awaiting the completion of prior tasks. If two or more operators simultaneously control the same object, the app processes the latest broadcasted goal. In the current version of our app, an operator must resolve this kind of conflicts through verbal communication with other operators. Fig. 3a shows a virtual object overlaid on the physical object. Fig. 3b demonstrates the rotation and translation of the virtual object. Fig. 3c and Fig. 3d represent the robots performing the task.

**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. 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 shows the virtual objects arranged in the environment.

**Robot Manipulation.** The app overlays a virtual robot over the real robot. The operator can manipulate this virtual robot to define its desired position. The color of the virtual robot resembles the color of the fiducial markers to identify and differentiate between multiple robots. The app allows the operator to move multiple robots through this gesture. Other robots belonging to the same team pause their operation until the selected robot achieves its defined position. If the robot is not part of any team, then the position change does not hinder any other operation of the system. If two or more operators simultaneously want to control the same robot, then the app processes the newest broadcasted goal. Also in this case the operators can resolve this kind of conflict through verbal communication. Fig. 5a shows a virtual robot overlaid on the physical robot. Fig. 5b illustrates the translation of the virtual robot.

**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 this virtual layer. The operator can manipulate this virtual 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. 6a and Fig. 6b shows the selection of a group of robots. Fig. 6c shows the manipulation of the virtual cube to define a new goal position for the team of robots. Fig. 6d indicates the robots positioning itself to the desired position.

**Team Reassignment.** A robot can be selected, and its virtual avatar can be moved to overlap with the virtual object. This gesture assigns the robot to the transport team corresponding to the object. This gesture is useful to increase the resources dedicated to a heavy object, to replace broken/damaged robots, and to distribute robot resources between multiple operators. Fig. 7a shows the virtual robot overlapping the physical robots. Fig. 7b demonstrates the reassignment of the team.
Fig. 7: Team reassignment through the interface to complete the task of moving an object. The overlaid dotted black arrow indicates the one-finger swipe gesture to move the virtual robot and the arrowhead color indicates the moved virtual robots.

Fig. 8: Collective transport state machine

D. Shared Awareness

The app broadcasts the modalities 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.

E. Collective Transport

We employ a simple collective transport behavior based on the finite state machine (FSM) shown in Fig. 8. This behavior is identical to the one presented in our previous work [21]. We omit its full description for reasons of brevity.

IV. User Study

A. Experimental Setup

We 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 we focus on the potential benefits of mixed granularity of control (MGOC), in our experiments we 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. Our 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. 9a shows the initial positions of the robots and the objects in the field.

Scenarios. As said, we 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, we established specific roles and modalities of interaction for the operators. We divided the field into two regions: the transport region (corresponding to Phase 1) and the placement region (corresponding to Phase 2). We 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 our previous study [21], in the transport region we allowed the operator to only use object manipulation. On the other hand, in the placement region, we allowed the operator to only use robot control. Fig. 9b shows the collective transport behavior in the transport region and Fig. 9c shows the robots controlled in the placement region. Fig. 9d 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.

Procedure. Each session of the study approximately took 75 minutes. Each session 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 min to explore the app. The participants answered a questionnaire after completing each scenario.

Participants. We 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.

B. Metrics

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

Workload. We employed the NASA TLX scale [58] on a 5-point Likert scale [59] for the participants to self-assess the workload during each scenarios. We also recorded the number of user interactions (e.g., number of touches and gestures on the app).

OOTL phenomenon. We evaluated the OOTL phenomenon by quantifying situational awareness, which is the main factor for its occurrence [11]. To quantify situational awareness, we employed the Situational Awareness Rating Technique (SART) [60] which measures attention demand, attention supply, and understanding of the task. Additionally, we recorded the activity period (AP) of the participants during the scenario to analyze the total duration of time they were active. We measured AP as the number of interactions (e.g., number of touches and gestures on the app) per minute.

Trust. We calculated the total trust in the system (operators + robots) by summing the perceived trust among humans and the perceived trust between humans and robots. We employed the group trust scale [14] to measure the trust between human teammates during a scenario, and the human-robot trust sub-scale [61] to quantify the trust in the robots’ behavior. We quantified all metrics on a 5-point Likert scale.

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

C. Results

Workload. Fig. 10a and Fig. 10b report the results of the workload comparison study for operators O1 and O2, respectively. 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 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. 11 which reports the median number of interactions made with the hand-held device for both tasks by operators O1 and O2.

OOTL phenomenon. Fig. 13a and Fig. 13b report the results of the situational awareness comparison study for O1 and O2, respectively. For O1, the SGOC scenario demands very 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 SGOC results in an OOTL phenomenon. In contrast, O2’s level of engagement and awareness is comparable across the two scenarios. This interpretation is compatible with the data shown in Fig. 12, which reports the length of the active period of both operators in each scenario.

Trust. The average value of the trust score is 50.92 and 53.85 for SGOC and MGOC, respectively. We performed a statistical test on the data, which revealed that the overall trust is higher in MGOC ($p = 0.039 < 0.05$).

Task Performance. Fig. 14 shows the box plot of task performance for SGOC and MGOC. The median time we observed was 10.74 min and 7.72 min for SGOC and MGOC, respectively. The data suggests that MGOC outperforms SGOC in terms of completion time.
VI. CONCLUSION AND FUTURE WORK

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

Our technological contribution is the first collaborative augmented-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.

Our scientific contribution 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.

Future work will aim to understand the effects of interface training on task performance [23], for instance, giving more time to understand and test interface before participating in the task. Additionally, we will aim at making the relationship between humans and robots more legible and transparent [62] and understand ways to keep the operators engaged in the system.

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