How are Your Robot Friends Doing? A Design Exploration of Graphical Techniques Supporting Awareness of Robot Team Members in Teleoperation

Stela H. Seo[1] · James E. Young[1] · Pourang Irani[1]

Abstract
While teleoperated robots continue to proliferate in domains including search and rescue, field exploration, or the military, human error remains a primary cause for accidents or mistakes. One challenge is that teleoperating a remote robot is cognitively taxing as the operator needs to understand the robot's state and monitor all its sensor data. In a multi-robot team, an operator needs to additionally monitor other robots' progress, states, notifications, errors, and so on to maintain team cohesion. We conducted a design exploration of novel graphical representations of robot team-member state, to support a person controlling one robot to maintain awareness of other robots in the team. Through a series of evaluations, we examined several design parameters (text, icon, facial expression, use of color, animation, and number of team robots), resulting in a set of guidelines for graphically representing team robot states in the remote team teleoperation.

Keywords Teleoperation · Robot state representations · Multi-robot monitoring · Team robot states · Interface design

1 Introduction

Teleoperated robots are becoming increasingly common and affordable, being used in situations where it can be difficult, dangerous, or expensive to send people. This includes search and rescue, military reconnaissance, exploration (e.g., deep sea), or industrial equipment inspection. Such situations are increasingly looking to use teams of robots, either with multiple people controlling a range of robots to provide better coverage (e.g., flying robot, high speed, different sensors),
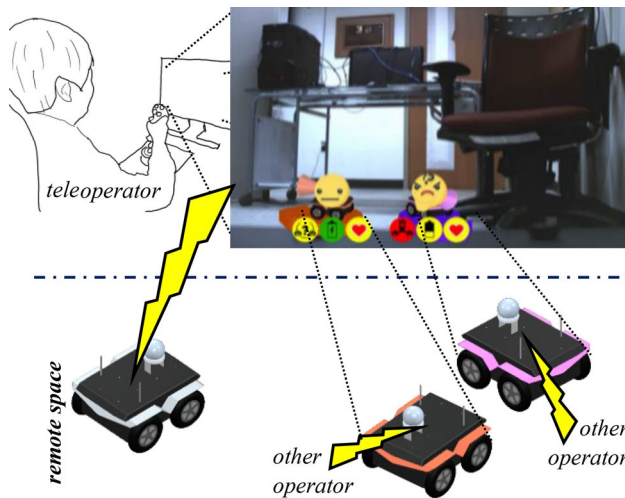
✉ Stela H. Seo
  stela.seo@cs.umanitoba.ca

  James E. Young
  young@cs.umanitoba.ca

  Pourang Irani
  irani@cs.umanitoba.ca

1 Computer Science, University of Manitoba, Winnipeg, MB, Canada

to reduce the human cost (i.e., one person controls multiple robots), or some combination of both [4, 40]. However, in all cases working with a team of robots necessarily increases the amount of information for operators to monitor, requiring more cognitive effort. This is a problem as user error remains a primary cause of mistakes in teleoperation scenarios [5, 13].

There is a range of potential approaches to teleoperating robot teams, such as overview interfaces that enable a single operator to manage multiple robots [14], multiple operators each using their own first-person view [8], or a single operator switching between active robots or views as needed [3, 9]. In this work, we address the common case where an operator is fully controlling one non-autonomous robot in a first-person view, and must maintain awareness of other robots in the team (and their actions) at all times.

This situation poses a range of interaction challenges such as ongoing communication with other human members, managing sliding-scale or mixed-initiative designs [13], supporting an operator when they context switch from controlling one robot to another [9], and representing the states and actions of robot team members in an easy to understand fashion. As an initial step, we focus on this last component, the specific awareness problem of an operator needing to maintain real-time awareness of other robots' actions and states, while themselves fully controlling one robot (see

Fig. 1 An operator teleoperates a robot located in remote environments, with two additional robot team members. While controlling one robot, they maintain awareness of other robots using on-screen widgets (screen bottom)

Fig. 1). Results to our work will be highly transferrable to a range of teleoperation situations, regardless of whether the other robots are partially or fully autonomous, controlled by another operator, or controlled by the same operator.

We designed a series of novel visualizations to represent states of other robots in a team, drawing from related work and human perception knowledge (Fig. 1). Through a series of exploratory studies using a mock teleoperation scenario, participants used our widgets to monitor the states of other (simulated) robots, while controlling a real robot. Specifically, we explored the use of text, icons, and emotional encodings, as well as the use of color, animation, and the number of team robots, to support awareness.

Given our exploratory focus we took a purposive evaluation approach, where we use small sample sizes across many conditions to gain initial insights into our design parameters. While this limits our ability to draw statistical conclusions from our data, it serves our purpose of exploring the broad design space. Further, the evaluation technique itself was exploratory, which we modified and adapted as we gained experience.

Our work results in a set of novel widgets for graphically representing robotic state, a testbed design for exploring teleoperation interfaces, and a set of initial guidelines for designing these interfaces. We further include a reflection on our evaluation methods with recommendations for ongoing work.

2 Related Work

In teleoperation, the user interface is a crucial factor for an operator's task performance [6, 29, 33] and situation awareness [11, 27, 33], as the user interface is the only gateway

that connects an operator and the remote teleoperated robots. Improving interface usability is an ongoing challenge for researchers to reduce human operator error for teleoperation problems [5, 13], to use human resources efficiently [23], and to reduce operator's cognitive load [29, 33]. Research solutions include improving robot automation (thus requiring less operator effort) [7, 30], control mechanisms [2, 16, 20, 24], and visual interfaces [29, 33]. However, we still do not fully understand how to design graphical widgets for representing a robot's state, or how to best design for multi-robot teleoperation interfaces to support an operator's awareness of other robots.

Interface designers and researchers have attempted to reduce the operator's cognitive load in many ways, including developing high-level (simpler) representations of complex data [34] that focus on task-relevant information [39], or visually drawing attention to important events [29]. Our work follows this common goal, in that we aim to design graphical widgets for high-level robot states to potentially reduce an operator's cognitive load.

In previous work in human–agent interaction, researchers found that good team work involves proactive responses to help team members [8] and positive engagements between team members [28]. In order to support these actions, the system must help a team-member operator to be aware of the states of others, helping them maintain high situation awareness. We pursue the same high-level goal by exploring how design elements can impact people's high-level awareness of team robot members in a cognitively taxing teleoperation scenario.

In human–computer interaction and human–robot interaction, researchers have explored icon representations [1, 12, 31] including emotional information encodings [26, 32, 35] in general. We extend this work by focusing specifically on multi-robot teleoperation interface designs.

Many teleoperation interfaces are built around the main video source. In video-centric interfaces, designers try to reduce interface occlusions [33] or simplify as much information as possible [34]. We follow the theme by aiming for small robot state representations with the high degree of information.

3 Graphical Representations of Robotic States in Multi-robot Teams

We explore novel graphical widgets to support an operator controlling one robot, and to maintain awareness of other robots' states in their team (Fig. 1). We focus on video-centric teleoperation interfaces, where the display shows a camera feed from the primary remote robot being controlled, and on-screen indicators and widgets present the additional pertinent information relating to other team robots.

To address these challenges, we first devise a set of robot states that represent broadly information pertinent

to working with multiple robots; we keep these generic to support generalizability across teleoperation contexts. Following, we explain our general visual design approach, and detail our specific strategies for encoding the given robot states into visual indicators in our interface.

3.1 Template Generic Team Robot States

The focus of our exploration is the case where a teleoperator is controlling a robot in real-time to perform tasks while simultaneously monitoring activities and states of other robots in their team (Fig. 1). We focus on general information that could be expected to be important across a broad range of teleoperation tasks involving multiple robots. With this in mind, we settled on representing robotic movement and activity, abstract task information, and basic robot state (Table 1).

3.1.1 Robot Movement and Actions

It is important to know the general movements and actions of other robot team members. We convey whether a robot is moving or not and its movement direction. Further, we convey robot camera look direction and movement, for example, in the case where a robot is not moving itself, but is carefully surveying a scene.

3.1.2 Abstract Task Information

To increase generalizability of our exploration we avoid targeted task-specific information (e.g., finding a victim, space coverage, inspecting equipment) and instead abstract task information to simply a robot having a message to share. We convey the state of whether there is no message available, a message is available, or an urgent message available.

3.1.3 Robot State

We selected three generic internal robot states we envision are broadly relevant in teleoperation: network connectivity, battery level, and system failure (or physical damage). Connectivity is important for expectations of responsiveness,

and whether the information shown is current. Battery level is common for all non-tethered robots and represents broadly ability to continue to function. Finally, robots are fragile and have system errors or receive damage from the environment, which can explain erratic or poor behavior.

While we accept the limitations of our generic robot state selection, and note the importance of continued exploration into more task- and robot-specific states, these generic states are useful for examining indicators across a range of teleoperation tasks.

3.2 On-Screen Visual Representation Strategy

To develop our on-screen widgets, we worked closely with a local design firm, ZenFri Inc., and held a series of informal design sessions. During our design meetings, we quickly converged on widget designs to represent the robot movement and actions, as this information is very simple to directly show in a visual fashion. As shown in Fig. 2, we use a 3D model of our particular robot, placed on a large direction arrow icon to represent orientation. The wheels move prominently to show movement, and the cone in front of the robot moves to indicate look direction and camera movement. Given the team consensus on this indicator we did not explore it further, and focused instead on exploring the abstract task information and robot state.

In our design sessions we settled on three main approaches for visual widgets representing team robots' states, that emphasize simplicity: short text messages, iconic
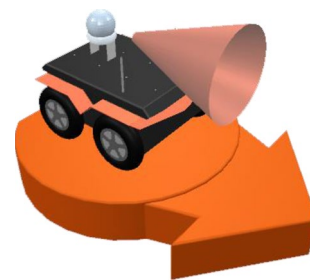
Fig. 2 A team robot indicator with its moving direction (arrow on the bottom) and look direction (cone on the top)

Table 1 General robot states. In our exploration, we explore variations of the four robot states: connectivity, battery level, physical damage, and mission messages. We abstract the details out to three categories

Robot movement and actions	Moving		Not moving	
	Looking around		Not looking around	
Abstract task information	**Mission message**	No message	Message	Urgent message
Robot state	**Connectivity**	Strong connectivity	Okay connectivity	Weak connectivity
	Battery level	Strong battery	Okay battery	Weak battery
	Physical damage	No damage	Light damage	Heavy damage

representations, or emotional encodings (emojis). Further, we explored whether the designs should be in color (with meaningful encoding) or greyscale, should be animated (to draw attention) or static, and how many robot widgets should be on a screen at once.

Using these representations and graphical visualization parameters, the team robot's four states are overlain on top of the robot model.

3.2.1 Text-Based Robot State Representation

We selected text as a standard approach to conveying information that is broadly understandable within a language group. Text further serves as a base case, an existing common approach, against which to compare our new methods. We would expect text to be slower than our other methods as it requires reading.

For simplicity reasons we restricted each state to be represented by at most two words (one descriptive adjective and one noun, Table 1). We tilted the text 45° (Fig. 3) to maximize its physical size within a small screen footprint, and to match the other methods used (square area). We added a black outline to maximize contrast and support readability

(Fig. 3). Text color was chosen to represent standard cultural meaning (e.g., green is OK, red is danger; see Sect. 3.3.1).

3.2.2 Icon-Based Robot State Representation

Icons can metaphorically convey a complicated message [12] and can be quickly understandable even when small or not in immediate attention [19] and while moving [21]; well-designed icons can quickly and clearly convey meaning. In comparison to text, we expect icons to be quicker to understand and perhaps easier to interpret.

For connectivity, we focused on showing robots being connected to each other, battery level uses a familiar partially-filled battery icon, physical damage uses hearts as is common in video games, and mission message uses a question mark to indicate the robot wants attention (Fig. 4). Icon color was chosen to represent standard cultural meaning (e.g., green is OK, red is danger; see Sect. 3.3.1).

3.2.3 Emotional Information Encoding

We developed emojis that use facial expressions to generally represent the overall combined robot state. As aggregated facial expression can be used to convey robot state and communicative signals [17, 25], by leveraging human

Fig. 3 Text representations for all states conveyed. Each state consists of two words: a noun and descriptive adjective. Text is tilted to maximize size within a square space, and we used a black outline to increase contrast and maximize visibility
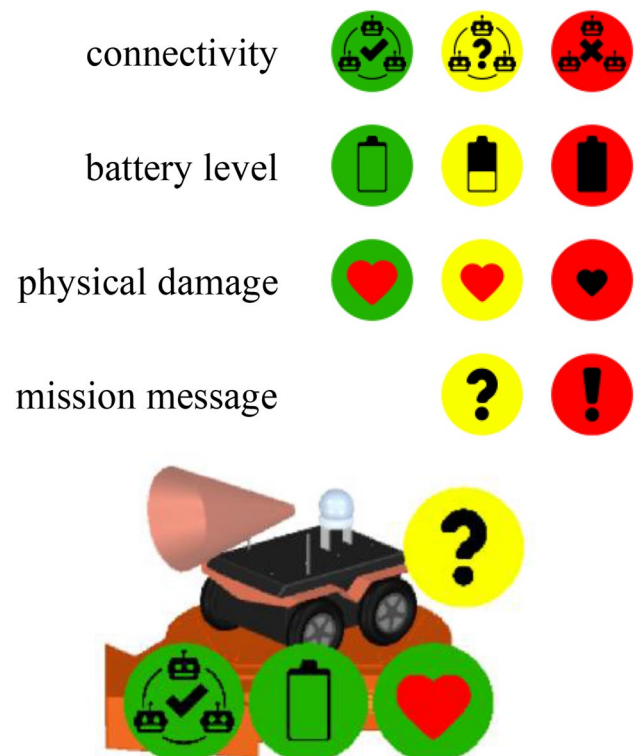
Fig. 4 Icon representations for each robotic state, with one-to-one mappings to the text. The icons are placed around the robot model, in the same position as the text indicators

social signal processing, we envision that adding emojis can increase communication bandwidth [35, 36]. With a team robot's facial expressions, we expect people to take a quick glance at the representation, build general idea of the robot's current states, and further increase their overall awareness.

Our team robot facial expressions (i.e., emojis on team robots, Fig. 5) aggregate all states into a single facial expression. For example, if all states are positive, the robot shows a happy emotion. We used two colors: red (angry) for overall negative states and yellow (all other emotions) for overall

Fig. 5 The emoji uses facial expressions to represent general states. The left faces above are for no message, the middle faces for message available, and right faces for urgent messages

positive or neutral states. We did not include green because a green face is perceived as a sick face.

3.3 Graphical Visualization Parameters

In parallel to our three design approaches (text, icon, emoji), we explore general graphical design parameters and their impact on the resulting widget: color coding (vs. greyscale), animation (vs. static), and a number of widgets on screen at once.

3.3.1 Color Coding of Robot States

Color can intrinsically carry meaning, or can be used simply to increase contrast and visibility [22]. However, it adds visual complexity and may be distracting. As such, we explore the use of full-color techniques versus greyscale variants (Fig. 6). In general, we mapped positive states to green, negative to red, and an intermediate to yellow, to follow common cultural standards.

3.3.2 Animated and Non-animated Icons

The movement and change in animation can draw a person's attention, to help them notice a state change or pay attention to a widget, but this can be distracting and impact performance negatively [29]. We investigate both static (perhaps not distracting, but may be ignored) and animated (may be distracting, but easy to notice) variants of our icon and emoji interface (Fig. 7). Our animated case is constantly moving like a game agent within the icon boundary.

3.3.3 Number of Team Robots

We anticipate that operator cognitive load will naturally increase as we increase the number of robot widgets on screen. To investigate this, we compare having one on-screen widget, representing having one team robot in addition to the
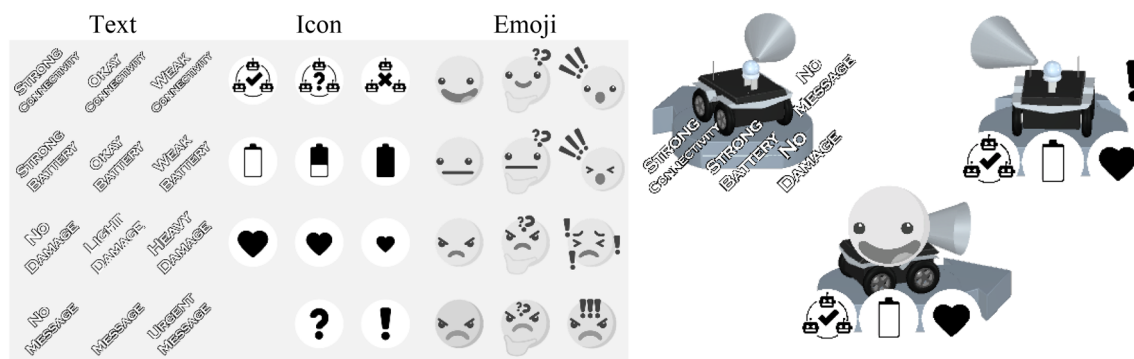
Fig. 6 Every asset, greyscale version: text, icon, and emoji representations. Examples with each representation shows on the right
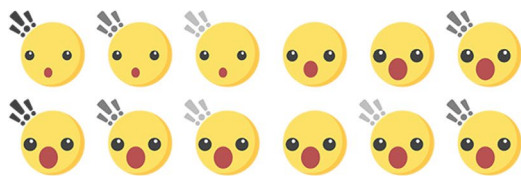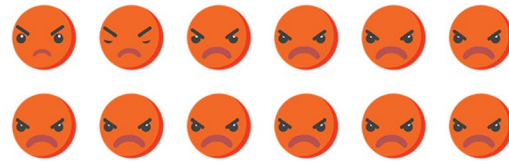
Fig. 8 Our team state representations for two team robots with emotional information encoding. Note that the message state is superimposed on the face

Fig. 9 A participant is unloading the robot. The mission goal and its progression are shown at the top center of the screen. Note that while the goal is always displayed, the progress bar only appears when the robot is at the designated location

operator's main robot, against two on-screen widgets, representing having two additional team members.

While the two widgets are functionally identical, they display different information as they are representing two different robot team members. Further, we changed the base color, with one robot eing orange, and the other being purple (Fig. 8).

4 Exploration Testbed

We developed a testbed to enable us to explore our widget prototype variants with participants. Our driving principle was to maximize ecological validity as much as possible, while balancing this with generic teleoperation tasks that can generalize across real-world applications. Our testbed includes a real robot and physical space to support navigation, and specific actions for participants to complete.

We target our testbed, and thus our exploration, to the specific case where a person teleoperates a single robot from a desktop interface, using an egocentric live video feed from the robot (Fig. 1). Following, the participant needs to monitor the state of one or two additional robots, which are assumed to be autonomous, using our widget prototypes (Fig. 8). We acknowledge that this limits our exploration specifically to single-robot egocentric robot control (in comparison to, for example, overview command interfaces), although we note that this remains a primary common interface for robot teleoperation.

Our testbed has a navigation task where participants have to navigate the robot between waypoints, action tasks where participants need to perform operations, while displaying the states of other robot team members in real-time on the screen (Fig. 9).

4.1 Robot Team-Member Simulation

Robot team-members were fully simulated, including their general navigation, look direction, and overall states. We generated the simulations using key frames consisting of a timestamp, robot state, position, and direction information. These were fixed across participants for consistency (e.g., in contrast to randomly generating robot states): all participants saw the same robot states and changes, in the same order and timing.

4.2 Navigation Task

We provided participants with a top-down map of the space (Fig. 10, displayed on a secondary monitor), and told them to navigate to a waypoint shown on screen. We designated six destinations in the space, which are clearly annotated on the map, as well as denoted in the
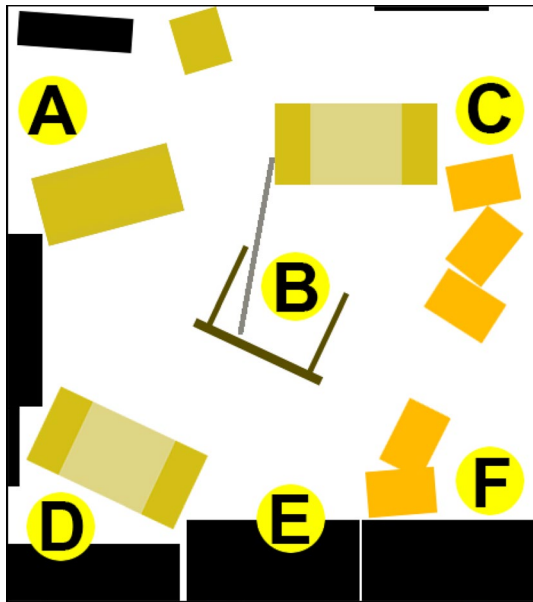
Fig. 10 A top-down map of the environment. Note the two underpasses under desks (lighter shading), obstacles, and designated locations. The map is displayed on a secondary monitor during studies, but the robot's current location is not marked

Fig. 11 Our on-screen questionnaire used to measure a participant's team state awareness. We did not include color coding in the questionnaire. When the questionnaire pops up, the teleoperation interface blacks out its screen, stops all processes, and waits for the questionnaire to be completed

real space using a paper sign on a wall or obstacle in the room (Fig. 9). We do not show the robot's position on the map to require the participant to engage the spatial navigation task, including localization and orientation, while avoiding obstacles. If robot collisions make major changes to the space (e.g., moving a table), the on-site, in-room researcher would quickly fix it while the robot was away from the obstacle.

4.3 Action Task

Our goal for the task was to require engagement from the participant, but not be technically challenging in any way specific to our robot or task. As such, we created simulated actions that only required participants to press a button rapidly, like a video game.

Our two simulated tasks were to load and unload cargo from the robot. Once the robot arrived at a designated waypoint, an on-screen message notes the required task (loading or unloading), and a progress bar is displayed (Fig. 9). When the participant presses a joystick button, the progress bar increases. However, it also decreases over time, requiring the participant to actively work to complete the progress bar. To avoid this task being too easy or difficult, our fill rate is adaptive, filling more per button press as time passes, to ensure that all participants can complete the task. Upon a completion of the task, the participant is asked to navigate to next designated location.

We designed this task to have some challenge, but to not be too frustrating, while providing a sense of achievement once completed.

4.4 Measurements

The primary purpose of our testbed was to evaluate how well our widget prototype designs enable people to maintain awareness of robot team member states, while fully controlling a robot themselves. Thus, we decided against the common practice of providing paper questionnaires at predictable times, as participants could prepare for them by focusing on the widgets, and even refer to the screen to answer questionnaires—this would measure widget legibility, not the ability for the widgets to support ongoing participant awareness.

Our solution was to build a questionnaire interface into our control interface. At unpredictable times, the interface screen would blank (hiding the screen and widgets) and a questionnaire would appear (Fig. 11), thus measuring ongoing awareness. We detail the specific questionnaires themselves in Sects. 5.4 and 5.5 as they evolved throughout our design exploration.

4.5 Implementation

Participants sat at a PC with two monitors, a 28-inch UHD monitor for our teleoperation interface and a 24-inch FHD monitor to show the map. Participant controlled the remote robot using a gaming joystick (jet fighter replica gaming joystick, Fig. 12, right). The monitor is positioned about 65 cm away from the participant, although we did not strictly

Fig. 12 Jackal UGV robot from Clearpath Robotics Inc. (left) and a gaming joystick (right) used in our design explorations

control this distance and participants could lean in or away. We placed the keyboard and mouse on a tray under the desk and the joystick on the desk; however, we allowed participant to change the initial desk setup for their convenience. Participants used the keyboard and mouse to complete the on-screen questionnaires.

We implemented our interface using Unity3D. Our robot, a Clearpath Robotics Jackal UGV robot (Fig. 12, left), is 43 cm wide, 51 cm long, and 25 cm tall, and about 17 kg, and is running on ROS indigo. We used a Point Grey Flea3 FL3-U3-13E4C-C with Tamron 1:1.4 8 mm ∅25.5 lens for the remote video.

5 Design Exploration

We conducted a 5-stage design exploration with variants of our widget prototypes and evaluation design. Given our exploratory aims, that is, to learn about a range of design parameters broadly and iteratively, we selected a purposive methodology where we conduct several variants with low numbers of participants. Our aim was to gain high-level feedback and insights across a range of features rather than definitive study results with more participants on fewer features. We recruited participants from our general university population, with each participant receiving $15 for their time. We conducted our design exploration using the testbed detailed in Sect. 4.

5.1 Exploration 1

This initial exploration aimed to investigate our primary overall variables. One, we wanted to compare our new widget designs to the text base case. Two, we wanted to test the animation (vs. no animation) and emoji (vs. no emoji, just icons). Further, this served as a feasibility test of our testbed and evaluation method.

5.1.1 Measuring Operator Awareness of Team-Robot States

Our general approach was to evaluate ongoing participant knowledge of the states of the robots represented by the widgets, to test if it supported maintaining awareness. We did this primarily by asking participants to recall the specific robot states. Figure 11 shows the initial pop-up format: it asks participants to report on all the elements we incorporated into the widget design. Note that this questionnaire only targets the one-team-member robot case.

We also asked participants to report their confidence in their score, to measure how much they felt they were guessing, and also asked them to explain the robot state in their own words, to see if they had a general awareness even if their exact state reporting was not correct.

5.1.2 General Questionnaires

Before the test, we administered a demographics questionnaire to collect participant age, biological sex, their 3D video game skill and play frequency, their vehicle driving skill and drive frequency, and whether they have previously participated in a study with robots.

After completing the teleoperation tasks with a particular widget design, we collected participant self-reported level of nausea, sense of task performance, how much the widget demanded their attention or was distracting, and helped them to maintain awareness. We also administered the NASA TLX [15] scale to measure self-report workload, and collected open-form written comments.

Post-study, after finishing all the conditions, we further collected participant preferences on representations, and free-form general thoughts on the widget and task.

5.1.3 Qualitative Investigation

For our design exploration goal, we planned to explore participant feedback on the post-condition and post-test written questionnaires. We conducted open coding on this written data with the goal of investigating what worked and did not work for participants, what items were confusing, and for exploring potential reasons behind performance differences.

5.1.4 Tasks

Participants completed the testbed task (Sect. 4) five times, with different robot widget designs: base case (text), and all four combinations of animated versus static and emoji versus just icons. That is, animated emoji, animated icon, static emoji, and static icon. In this design exploration, all representations were provided in full color.

We fixed each condition at 6 min and 30 s long excluding the time taken to answer the pop-up questionnaires, which

appeared at pre-defined intervals (but unbeknownst to the participant); the number or timing of questionnaires was not communicated to participants. Our task was sufficiently long that all participants would require more time than allocated, enabling us to end the experiment after the same duration for all. The pop-up robot state inquiry questionnaire appeared three times per each condition.

5.1.5 Procedure

After participants arrived, we introduced the idea of teleoperation and motivated the need for an operator to control one robot while monitoring others, generally explaining the challenge of minimizing the required cognitive load. We administered the demographic questionnaire and provided a training session on how to control the robot using the joystick. During training, we further introduced the concept of monitoring the other robots in the team, the states that the robots were communicating, and how our widget were designed to convey those states. We explained the teleoperation tasks and gave an example of what the pop-up questionnaire would look like. We provided ample time for the participant to learn the interface and widgets, until they themselves indicated that they were ready to move forward.

Participants completed the testbed task with all five conditions; the order of conditions was counterbalanced using an incomplete Latin square. At the beginning of each condition, the researcher reminded the participant of the condition, the requirement to maintain awareness of the team robot member, and provided an opportunity for them to ask questions.

After each condition, we administered the post-condition questionnaire. At the end of the study, we administered the post-test questionnaire.

We recruited 15 participants from the general university public.

5.1.6 Results

The primary theme that emerged from our qualitative analysis was that participants tended to comment on how easy a technique was to understand. Five of the 15 people indicated that they felt the text method conveyed meaning precisely, *"words are a much much more clear [sic] interpretations comparing with icons"*—P7 and *"I don't need to think [with Text]"*—P12. This corresponded to the same participants rating the text as the one they liked the most.

In contrast, others (10 out of 15) noted that the icons and emojis require less effort than text: *"the text representation involved mentally deciphering the words and the color code associated with those words"*—P1 and *"I preferred the icons over the text because I found it easier to look at*

a picture representation than to read words while trying to complete a task"—P9. This also matched the participants who did not list text as their preferred method.

Many people (7 of the 10 who did not prefer text) noted that the emoji facial expressions added confusion: *"I prefer the simple icons over the ones with character, because for me the ones with character was confusing me"*—P6 and *"the face is not clear and it is very big"*—P11. However, three of the 10 did find that the emoji provided an overall view on the state: *"with character makes it easy to understand the overall situation of team member"*—P4 and *"because it [Static Emoji] is easily to recognize and receive by specific characters, colors, than words description"*—P5.

Many people (7 of the 10) preferred the static representations over the animation. Negative comments toward animation were *"static can help in avoiding distractions"*—P4 and *"the animated icons made the screen too busy so that I was feeling stressed and overwhelmed and couldn't focus on the task at hand as well"*—P9. There were some positive comments toward the animations: *"I prefer the animation over static because animation grabbed my attention better than with just static. Also, you can see which state it is in in the corner of your eyes while trying to finish the given tasks"*—P6.

For our quantitative analysis we note that given our small sample size (15) we have limited ability to draw concrete conclusions from our statistical results. We conducted ANOVAs to test the impact of our widget designs on our measures.

First, we conducted one-way ANOVAs with planned contrasts, comparing our new widget designs (animated emoji, animated icon, static icon, and static emoji), against the text base case. We found no effect of interface on recall of robot state, participant confidence, or nausea. We did find an effect of widget type on TLX performance subscale ("How successful were you in accomplishing what you were asked to do?", $F_{4,56} = 2.99$, $p < .05$, Fig. 13). Planned contrasts revealed that participants felt they performed worse with static emoji ($F_{1,14} = 4.78$, $p < .05$, $M = 7.87/20$, $SD = 5.14$—lower numbers indicate better result) than text ($M = 5.53$, $SD = 4.47$). We did not find any other effects.

We further conducted two-way ANOVAs, excluding the text case, to investigate our two design dimensions; animated versus static by emoji versus icon-only. As above, we found no effect of interface on recall of robot state, participant confidence, or nausea. We found a main effect of emoji (emoji vs. non-emoji) on participant reported TLX performance ($F_{1,14} = 5.92$, $p < .05$): people reported that they performed worse with emoji ($M = 7.07/20$, $SD = 4.06$—lower numbers indicate better result) than non-emoji ($M = 5.00$, $SD = 4.04$). We did not find any other effects nor interaction effects.
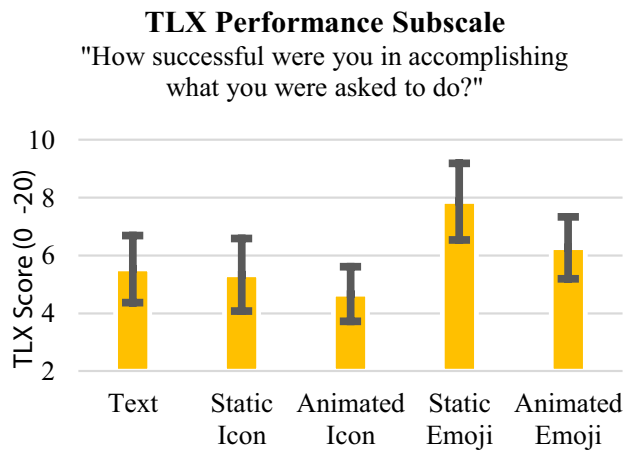
Fig. 13 Exploration 1 NASA TLX performance subscale report. Error bar indicates the standard error. Lower scores are more positive

Fig. 14 Our on-screen questionnaire used to measure a participant's team state awareness for two team robots. High-detail versions are in the appendix

5.1.7 Lessons and Next Steps

Our qualitative data generally supports our design approach, that most participants seem to find the icons less mentally demanding than the text. However, about a third of participants felt otherwise, and thought that text was a reasonable approach. Our inconclusive quantitative results do not provide further insight, as no interface seemed to perform better than any other.

Regarding animation, participant consensus did seem to be that the distraction of motion was a detriment, although some noted the benefits of pulling attention. Further, despite some participants noting benefits of the emoji, both the qualitative and quantitative data suggest that overall people may find them confusing and more difficult to interpret.

Our biggest concern with the data was the apparent lack of performance results, on how well participants were able to recall the robot states that they were monitoring—we have no evidence that any design performed better (or worse) than others. Looking at the data, we first noted that the robot was constantly moving and looking around, making it somewhat difficult for participants to answer those state points. However, re-conducting our analysis without these measures did not yield results. Further, we found that while the overall average accuracy was 63%, some participants managed to obtain 100% recall, suggesting a potential ceiling effect on our measurement. Of particular note is that we have no evidence of text yielding worse performance than the other methods, despite our expectations.

As such, to follow up we decided to test the same experimental design with more robots, to increase the difficulty and avoid the ceiling effect, while simultaneously investigating the impact of monitoring more than one robot team member.

We also note that some participants noted the effect of color, which was one of our design approaches; we re-visit this in a later stage.

5.2 Exploration 2, Two Team Robots

We conducted a second exploration to investigate the impact of requiring participants to monitor two robots, with two related on-screen widgets (Figs. 8 and 9) and the expanded questionnaire (Fig. 14). We followed the exact same procedure otherwise as above, in Exploration 1. We recruited 5 pilot participants and compared new results to the first exploration.

5.2.1 Results

Our qualitative analysis uncovered a clear difference relating to the task difficulty, where some participants complained of the complexity, which was not raised in the same fashion in the previous study: *"there are too many things to look out for at the same time"*—P21. Given the low participant count we did not conduct statistical significance. However, the average recall performance dropped by about 10% (from 63 to 53%), and overall NASA TLX score increased from average 7.87/20 to 10.93/20. Despite the lowered state recall accuracy (moving away from the potential ceiling effect) we still did not see any indication of clear performance difference between widget designs.

Text also did not perform more poorly, as we expected it may. One participant linked this to our performance measurement instrument: *"it is easy to remember while answering the questionnaire"*—P21.

Other results echoed what we found in Exploration 1, where participants praised the use of color coding, *"same*

color represents same status is very good"—*P23*, and others commenting generally on the icons, *"icon is easy to understand and simple and static can make me easy to find the moving and looking around information"*—*P23*. One person also noted how the animated icons drew their attention in a positive fashion: *"it was easier to interpret without focusing too much"*—*P24*.

5.2.2 Lessons and Next Steps

Our results indicated that the addition of a second robot did indeed impact participant perceived task load and performance on the state recall task (with the caveat that we do not have statistical significance). However, despite this we did not see a difference in performance across our interface designs, with text still not performing more poorly, contrary to our expectations. However, one participant provided a potential hint, noting that the text in the questionnaire matches that specific interface design.

In considering our participant feedback, we noted that color may provide a memory cue, and also that participants may be able to monitor the color (and changes) using their peripheral vision. This further motivates the exploration of color versus greyscale variants.

5.3 Exploration 3, Greyscale Variants

We conducted a greyscale pilot, with 5 new participants, to enable us to compare against our color results to date. Our greyscale variants force participants to interpret the icon or text data instead of relying on color only. We maintained the same procedure from Exploration 1, which only included one robot to monitor.

5.3.1 Results

The overall results in the greyscale study matched what we found in the previous explorations. The recall accuracy was 59%, with TLX load reported as 10.78/20 on average.

Participants prominently compared techniques against text, noting the ease of interpreting the icons, *"because it is less demanding on the visual processing, has little to no distraction, gives room for better mental representations for the individual, which is absent in textual forms"*— *P30*. With two particularly noting the benefits of text: *"the words allowed me to understand the icons more quickly"*— *P28*. Finally, feedback on the emoji was generally negative, for example, *"emoji was hiding the movement of the robot"*—*P29*.

5.3.2 Lessons and Next Steps

We found similar results with the greyscale widget versions as with the color; the minor differences found (in the direction of greyscale being slightly harder) does not suggest that we need further inquiry involving more participants and statistics. Importantly, this result does not provide support for the idea that participants may be relying heavily on color only for monitoring robot state. We still believe that color is beneficial for our motivational reasons, supported by qualitative feedback, but these results suggest we do not need to investigate further.

Based on participant feedback focusing on text, in particular, participants making an explicit link between our widgets (with text shown) and our evaluation instrument (where they select the exact same text), we noticed a potential confound in our study design. In the text interface case, participants simply match the words from the widget to the questionnaire, while in the icon cases, they need to remember the meanings of the icons and do a translation to the text on the questionnaire. This may provide an advantage to the text case and would explain our results, as we expected text to perform more poorly. To investigate this, we update our evaluation instrument for the next exploration.

5.4 Exploration 4, Improved State Questionnaire

Drawing from our realization of the text-based questionnaire being a potential confound, we re-designed the questionnaire to match the designs of the widget interfaces. That is, we kept the text-based questionnaire for the text widget case (as already shown, Fig. 11). For the icon and emoji conditions, we modified the questionnaire to show the specific items to match the widget designs (Fig. 15). We removed any state-specific information (e.g., color, facial expressions for emoji) to make them generic.

We followed the same procedure as in previous explorations, with an additional emphasis placed on participant training for answering the questionnaires to ensure they understood the new additions. We kept the full color widgets, but used the two-widget case (to monitor two robot team members) to avoid potential ceiling effects as noted earlier.

We recruited 10 participants to test the matching option questionnaire; the additional amount (compared to 5 participants for previous phases) enables us to do statistical exploration.

5.4.1 Results

We start with our quantitative results to investigate on the impact of the new evaluation instrument approach. We first used one-way within-subject ANOVA tests with planned contrasts to compare our new widget designs against the

Fig. 15 Our modified questionnaire with the icons that match to the widget designs. Only portions of the questionnaires are shown, full versions can be found in the appendix

text base case. We did not find any statistically significant effect of interface on any measure taken, including recall performance or self-report workload. The average performance was 42%, and average TLX response was 12.05/20.

We conducted two-way repeated measures ANOVA tests to investigate the impacts of our animation and emoji dimensions (animated vs. static, and icon only vs. emoji), excluding the text base case. We found a main effect of animation on the TLX effort dimension ("How hard did you have to work to accomplish your level of performance?"). Participants reported that the animated interfaces ($F_{1,9} = 7.57$, $p < .05$, $M = 15.05$, $SD = 3.85$, Fig. 16) required more effort than the static ones ($M = 13.75$, $SD = 4.22$). We note however that it appears that the weak performance of the animated emoji condition may be driving the result.

Our qualitative feedback again echoed prior studies. Comparison with the text method was an overall theme, with a half of our participants clearly preferring the text method, for example, because *"ICON is hard to memorize. I honestly prefer the color not the texture itself"*—P34 and *"it is much more clearer in sending the message"*—P35. Those who did prefer the icons noted that it is *"because it's easy for me to see and does not distract me from the task"*—P31.

Again, as previously, participants noted the difficulty with the number of states, for example, *"two team members are too much. I could remember only one of them"*—P40.
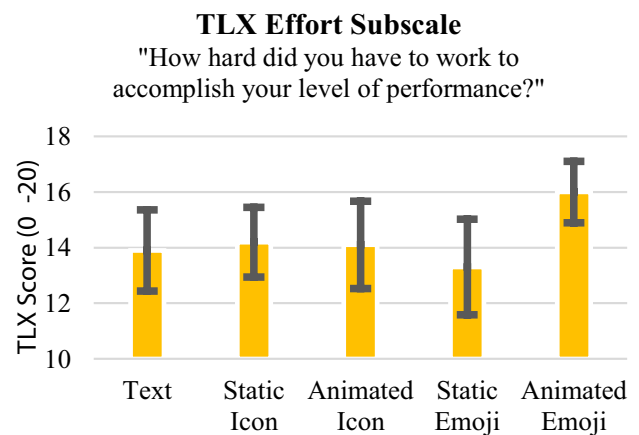
Fig. 16 Exploration 4 NASA TLX effort subscale report. Error bars indicate standard error. Lower scores are more positive

5.4.2 Lessons and Next Steps

We did not find an improvement on performance or any change in results despite our improved questionnaire design; on the contrary, we found a stark decrease, although we did not conduct statistics on this change due to the small sample size. We do highlight that earlier indications of high workload were echoed here, with participants noting the difficulty of keeping track of everything. As

such, for the last exploration phase we drop this questionnaire and explore a slightly different approach to measuring awareness of state.

5.5 Exploration 5, Alternative Questionnaire

In an attempt to gain a more accurate measure of how well participants can maintain awareness of robot states using our widgets, we made important changes to our protocol.

First, instead of having our pop-up questionnaire ask about the entire robot state at once, which adds a time delay for the person to recall by the end of the questionnaire, we reduced the pop-up to only inquire about one aspect of the robot state at a time (Fig. 17). It would only ask about one of the robots at once, and inquire about either connectivity, battery level, damage, or message. In addition, we asked for an overall sense of the robot well-being. We removed questions about moving and looking around; as previously mentioned, the robots are always moving or looking around, so these were less valid.

Second, we aimed to collect more data to both compensate for the reduced detail of the pop-up questionnaire, and to increase the accuracy of our result. Given the strong indication in earlier studies of animation being distracting, we only kept the static conditions for this iteration. We did keep the emoji despite negative results, as given the novelty of the approach we wanted to collect more data. Thus, we have three conditions: text, static icon, and static emoji.

As a result, to keep the entire experiment length similar despite fewer conditions, we extended the task time from 6 min 30 s to 10 min, and increased the count of pop-up questionnaire from 3 to 8, to collect more data. We recruited 6 people to participate.

5.5.1 Results

The overall accuracy dropped to 21%, with TLX score averaging 10.15/20. No additional insight was gained from the qualitative analysis.
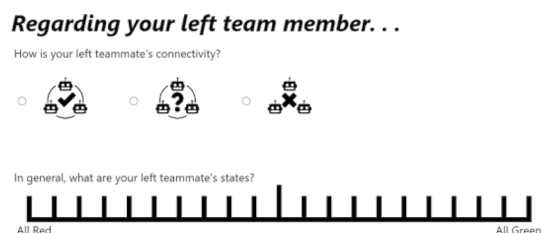
Fig. 17 Our stripped-down questionnaire, which only asks one state of one team robot and the robot's general well-being

5.5.2 Discussion

Our new state measurement technique reduced participant accuracy dramatically (from 63% in Exploration 1 down to 21% here), with TLX scores remaining about the same as the other explorations. Reflecting back, we conducted a post hoc meta-analysis of participant performance scores across our evaluation methods. That is, we compared our original pop-up questionnaire that always showed text states, against our revised version that showed icons, and against our final reduced questionnaire; this meta-analysis only included the test, static icon, and static emoji cases to enable us to include Exploration 5. We note that this is a post hoc analysis across studies (which several confound variables); we do not make statistical claims but rather use this for informing our future inquiry. A one-way ANOVA reported an effect on state report accuracy ($F_{2,38} = 29.84$, $p < .05$), where participants reported more accurately with the initial, all-text questionnaire ($M = 61.5\%$, $SE = 2.47$) than the matching questionnaire with icons ($M = 41.7\%$, $SE = 3.90$) and the final simpler questionnaire ($M = 20.8\%$, $SE = 5.04$).

6 Guidelines for Graphical Widgets Representing Robot Team Member States

We summarize our overall findings resulting from our five-stage design exploration. Overall, all representations we created helped people to maintain awareness of team robot states to a similar degree, with no obvious winners or losers. The primary unexpected finding was how well the text representation fared.

6.1 Design Guidelines

6.1.1 Text is a Viable candidate

Short one- or two-word text state representations performed as well as icon representations. While one may assume that text is slow to read, perhaps with short text it can become similar to an icon and easily recognizable (iconification).

6.1.2 People Feel Icons are Easier

More than half of the participants reported that they prefer icons and emojis, despite a lack of clear performance increase. According to their comments, participants felt that icons were easier to understand. Consider using icons in cases where people's perception of workload is important.

6.1.3 Anthropomorphic Representations may not be Clear

While some enjoyed the faces, most participants reported that the emotional encoding information was not clear, and in some cases distracting.

6.1.4 Animation: Balance Distraction with Attention Grabbing

Participants generally reported that animation could be distracting, although a clear minority found them attention-grabbing in a positive way. This supports prior work [29] on balancing distraction.

6.1.5 Color is Good to Show the Level of Robotic States

Participants found color coding to help maintain awareness of team robot states, as the color distinguishes the level of states (severity or urgency). We recommend teleoperation interface designers to use color coding for the level of robot states if applicable.

7 Discussion and Future Work

We designed a set of novel visual widgets to represent generic robot states in a teamwork teleoperation scenario. Overall, the widgets performed acceptably well, and through our exploration, we identified an outstanding core challenge in how to assess the utility of such widgets to help operators maintain awareness of robot states.

The surprise in this work was that the text base case performed as well as the other methods. One potential explanation can be iconification, where the short text becomes an icon of sorts: our text state has color and two simple words.

Another surprise was the lack of correlation between what participants thought of their performance, and their actual performance or self-report workload (NASA TLX) report. It will be important to further explore what impact this participant perception may have on overall task performance. Perhaps we could further extend our assessment method, for example, by using reaction time [10, 37] or pupil dilation [18, 38].

We note that the opinions on our animated icons were mixed. In retrospect, we note that the animated cases were always moving, instead of only animating when needed (e.g., to draw attention to a state change). Further, our emoji icons did not perform well overall. Despite the promise of emotional encoding leveraging the person's social interaction system, perhaps the introduced level of abstraction simply created confusion. This limitation, and further how to explore leveraging social interaction without creating vagueness, is important for future work.

Looking forward, one of the biggest remaining challenges is how our widget approach will scale to larger teams. We only tested with two on-screen widgets, and the required visual real estate will become increasingly prohibitive as we move to five, ten, fifteen robots, or more. Perhaps in this case, similar to how we abstract sensor data into simplifications to convey general status, groups of robots could be represented by a single or meta-widget that aims to encapsulate high level health and status of particular teams. For example, perhaps a small swarm of robots could leverage characteristic movements (as in [35]) to convey fatigue or confusion. Alternatively, robots that do not require any attention (all systems OK) perhaps do not need to be displayed, only those which have something to communicate: this would reduce the on-screen clutter. Regardless, consideration of how this approach may work for large robot teams is crucial for future work.

Overall, we felt that our testbed was a success, despite challenges faced with evaluating awareness and performance. This measurement problem is not solved (that is, measuring how well the widgets help people to be aware of team robots), and additional methods need to be investigated. The testbed itself could be improved, for example, by incorporating mission-relevant information such as the other robot states into participant actions; this may increase motivation to maintain awareness of their states.

8 Conclusion

This paper presents a novel approach to representing the states of robot team members in multi-robot teleoperation tasks, including a series of new widget designs and

prototypes for representing general robot state. Despite mixed results, we note that all instances were successful in supporting operator awareness, speaking to the general potential of the approach.

Further, we developed a novel team teleoperation scenario testbed, that is reasonably generic and can be used by others for teleoperation interface exploration.

The results from our design exploration provide a depth of insight into how teleoperators may respond to a range of visual design parameters including animation, color, and emojis. Drawing from our five-stage study including 41 participants, we present a set of guidelines for graphically representing robot team member's states that can aid future work in the area.

Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix: State Inquiry Questionnaire (All Text Options): One Team Robot/Text Representation

Appendix: State Inquiry Questionnaire (All Text Options): One Team Robot/Text Representation

Appendix: State Inquiry Questionnaire (Matching Options): One Team Robot/Icon Representation

Appendix: State Inquiry Questionnaire (Matching Options): Two Team Robot/Icon Representation

Appendix: State Inquiry Questionnaire (Matching Options): One Team Robot/Emoji Representation

Appendix: State Inquiry Questionnaire (Matching Options): Two Team Robot/Emoji Representation

Appendix: State Inquiry Questionnaire (Simpler Version): Left Team Robot/Text Representation

Appendix: State Inquiry Questionnaire (Simpler Version): Left Team Robot/Icon Representation

Appendix: State Inquiry Questionnaire (Simpler Version): Left Team Robot/Emoji Representation

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Stela H. Seo is a Ph.D. candidate in the Department of Computer Science at the University of Manitoba. His research focuses on investigating novel interface techniques for controlling robots in individual or teamwork scenarios, especially using enhanced visualization and social cues.

James E. Young is an Associate Professor in the Department of Computer Science at the University of Manitoba. His research focuses on investigating new ways for people to work alongside robots, with a special focus on robots that use social interaction modalities. He received his PhD from the University of Calgary in 2010.

Pouraing Irani is a Professor in the Department of Computer Science at the University of Manitoba. His research lies broadly in the areas of human–computer interaction and information visualization. He concentrates on designing and studying novel interaction methods and systems for giving end-users efficient access to diverse information types and through a variety of computing devices while evaluating their efficacy under different contexts and environments. He received his Ph.D. from the University of New Brunswick in 2002.