Robot Visualization Algorithm

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***Abstract*—Prior results have demonstrated that moderating the saliency of information items on a map-based interface for robot teleoperation can help to reduce cognitive workload and improve user performance. This paper presents the Robot Visualization Algorithm (RVA) for moderating the saliency of robots on a map-based interface for robot teleoperation by first responders in a disaster response situation. This paper also presents results from a within-subject evaluation to investigate the strengths and weaknesses of the RVA in comparison to a baseline visualization algorithm.**

I. Introduction

Modern robotic systems are used in a broad range of domains and vary widely in their capabilities. For example, some robots are designed for aerial photography and equipped with cameras and rotors, while other robots are designed for military use and equipped with firearms and various forms of sensors. The versatility of modern robotic systems allows them to particularly excel at tasks that may be considered too difficult or too dangerous for humans to perform.

Due to the spectrum of tasks for which robotic systems may be used, robots may have many levels of automation, ranging from pure teleoperation, or remote control, through varying levels of autonomy [13], [14]. Teleoperation requires one or more human operators to specify all of the robots actions, and would be particularly apt for situations where decisions need to be made based on information outside the robotic systems' knowledge. Mediated teleoperation allows the robot to execute predetermined sequences of events, resulting in a supervised robot that executes simple automated behaviors.

Due to the effectiveness and teleoperability of these modern robotic systems, response teams to Chemical, Biological, Radiological, Nuclear, or Explosive (CBRNE) emergency incidents are evolving from teams comprising humans with equipment to teams comprising humans and semi-autonomous machines. Unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs) can be used to extend the capabilities of a first responder team to a disaster event. When an emergency incident occurs, the first responder team can send out UAVs to survey the incident area for obstacles or victims. UGVs can also be used in areas where it might be too dangerous for a human responder to venture, such as the location of a radiological accident. In order to make the best use of these robots, first response teams usually dedicate an unmanned vehicle specialist (UVS) to control and direct the unmanned vehicles. Pure teleoperation of the robots would be undesirable. A UVS controlling multiple unmanned vehicles will easily be overwhelmed with controlling each individual robot. Full autonomy of the robots would also be infeasible due to the amount of uncertainty present in a disaster response situation. Thus, the UVS requires an interface that effectively facilitates mediated teleoperation.

In designing user interfaces for robot teleoperation, map-based visualizations are often included as they can improve situational awareness by supporting the users understanding of the robots location in relation to its surroundings [5], [7]–[10], [15]. Each team of first responders may control their own set of robots from their own interfaces, but it is also important for the teams to share information. If multiple teams of semiautonomous robots are to be controlled by one or more teleoperators, the number of robots displayed on the map increases proportionally. This affects the information density of the map, or the number of information items in an area of a map relative to the screen size of that area of the map. When many robots are deployed in a single system, not all robots may be equally relevant to all UVSs at all times. A UVS teamed with a small subset of robots needs less information about the robots of other teams, thus making the robots of other teams less relevant. A UVS supervising a swarm of tens or hundreds of robots cannot directly attend to all robots at all times. It is thus crucial to increase the saliency of more relevant robots to reduce the UVS's cognitive workload.

The Robot Visualization Algorithm (RVA) is a map-based robot visualization strategy that has been designed to moderate the saliency of robots based on relevance, but can also incorporate neglect time to further ease the cognitive demands placed on a user. Neglect time is the amount of time a robot is predicted to operate without supervision before performance degrades below an acceptable level [3], [12]. Incorporating neglect time into the RVA will ease the cognitive demands on the user by automating the task of tracking the time that elapses between user interactions with the robot. More general models [6] have been shown to reduce cognitive workload and improve user performance, so extending the convention to moderate the saliency of robots will provide the same benefits and keep the display consistent, which will promote ease of learning [11].

II. Robot Visualization Algorithm

The RVA was designed with one important requirement in mind: the RVA should reduce the cognitive workload of the user. In addition, the RVA should maintain or preferably

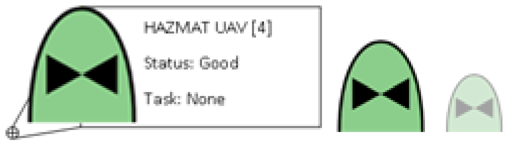


Fig. 1. Detailed, Normal, and Residue visual states in order.

improve the user's situational awareness. To do this, the RVA calculates a visual score for each robot that determines how it will be displayed. The visual score is a bounded continuous value ranging from 0 to 100 that represents the relative importance of a particular robot. Based on its visual score, a robot can be displayed in one of three visual states: detailed, normal, or residue (see Fig 1.). Robots that are not on a UVS's team, i.e. out-team robots, are displayed in residue state by default and robots that are on a UVS's team, i.e. in-team robots, are displayed in normal state by default. If a robot's visual score exceeds a certain threshold, it will be displayed in a "higher" visual state. The RVA algorithm is shown in Algorithm 1.

Algorithm 1: Robot Visualization Algorithm

```
for each time step:
    for each robot, r:
        compute the robot's visual score, v_r.
        if v_r ≥ v_{r, details}:
            display the robot, r, in detailed state
        else if v_r ≥ v_{r, normal}
            display the robot, r, in normal state
        else:
            if v_{r, residue} > 0:
                display the robot, r, in residue state
```

where:

$v_{r,\text{ details}}$ is the minimum visual score required for a robot to be displayed in detailed state.

$v_{r,\text{ normal}}$ is the minimum visual score required for a robot to be displayed in normal state.

$v_{r,\text{ residue}}$ is a Boolean value that determines whether or not a robot is eligible to be displayed in residue.

The RVA calculates a visual score for each robot on the map as follows. Starting with some initial visual score, the visual score in the next time step is calculated by subtracting a decay constant and adding the a value based on six components in four classes. If the decay constant is greater than the added value, the visual score decreases. If the decay constant is less than the added value, the visual score increases. The seven components comprising the added value are shown below.

$$v_1 = v_0 - \text{decay constant} + max \begin{cases} k_1 * [\text{proximity to high risk objects}] \\ +k_2 * [\text{proximity to in-team robots}] \\ +k_3 * [\text{hover event}] \\ k_4 * [\text{neglect time expiration}] \\ k_5 * [\text{fault status}] \\ k_6 * [\text{out-team operator trigger}] \end{cases}$$

where k_n, n = 1, 2, etc., denotes the scalar constants representing the relative importance of each component. Each component is explained in more detail below.

1) Proximity to high risk objects: This component applies only to in-team robots. It is a continuous value calculated based on the distance between an in-team robot and all other high risk objects displayed on the interface. Each object on the map would have some radius within which it was considered high risk. Within this radius, proximity is calculated as the Euclidean distance between the latitudes and longitudes of the robot and the high risk object.

2) Proximity to in-team robots: This component applies only to out-team robots. It is a continuous value calculated based on the distance between an out-team robot and all in-team robots displayed on the interface. Each in-team robot on the map would have some radius within which it would affect an out-team robot's visual score. Within this radius, proximity is calculated as the Euclidean distance between latitudes and longitudes of the in-team and out-team robot.

3) Hover event: This component applies to robots on both teams. This component is a Boolean value determined by whether or not a user's cursor was positioned over a particular robot.

4) Neglect time expiration: This component applies only to in-team robots. This component is a Boolean value determined by whether or not the neglect time for an in-team robot has expired. An in-team robot that has had its neglect time expire will have its status change.

5) Fault status: This component applies only to in-team robots. This component is a Boolean value determined by whether or not an in-team robot has a malfunction. An in-team robot that has had a fault will have its status change.

6) Out-team operator trigger: This component applies only to out-team robots. This component is a Boolean value determined by whether or not one team's UVS had forced their robot to have greater importance on another team's UVS interface.

These components combined with their scalar weights determined the visual score of a particular robot. The values assigned to each scalar weights will vary based on the needs of the system in which the RVA is deployed.

III. Apparatus/Methods

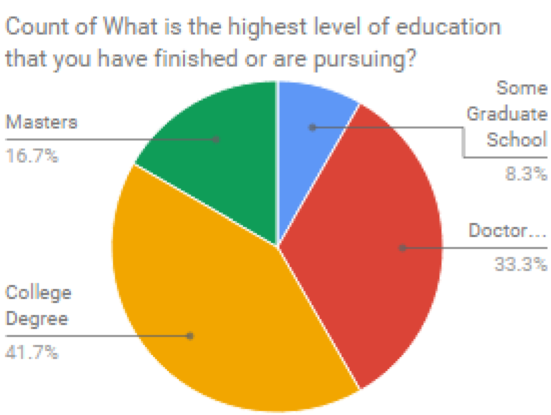
The RVA was evaluated by comparing it to a baseline visualization algorithm, the BVA. With the exception of the hover event, the BVA essentially held the visual score static at zero: in-team robots would be displayed in Normal state and out-team robots would be displayed in Residue state. The hover event was kept in the BVA so that the participants would still have a way to check if the robot had malfunctioned or not. This allowed for a measure of the effectiveness of the RVA in reducing cognitive workload.

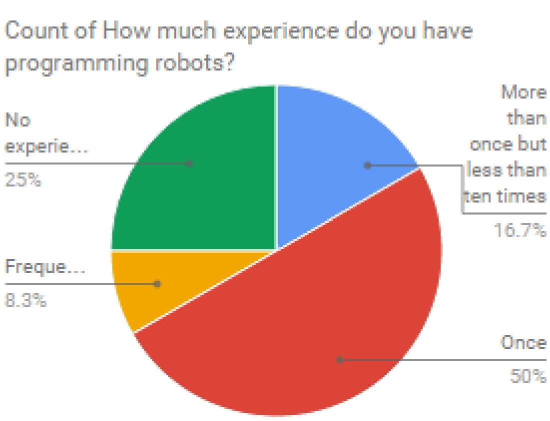
A. Participants

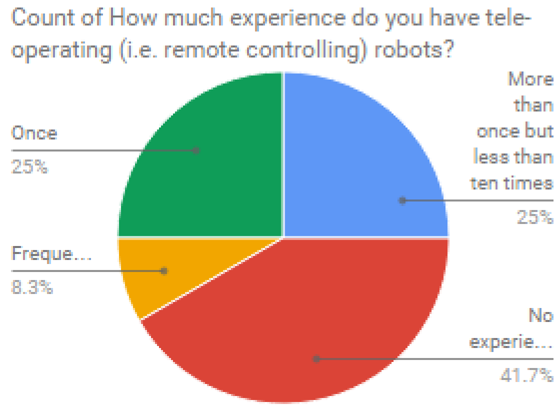
A total of twelve participants were involved in the experiment. Participants were selected based on the following criteria:

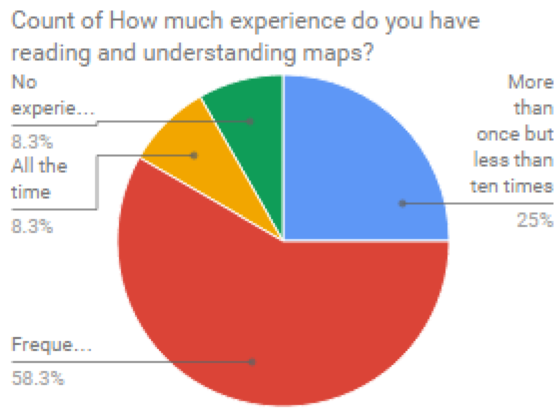
- Lack of knowledge of and experience with the RVA and its superset, the System of Human-Robot Interfaces (SHRI).
- Normal or corrected-to-normal color vision.
- Normal dexterity with at least one hand, either right or left, adequate for using a mouse cursor positioning device.
- No specific gender or age requirement.
- Willingness and enthusiasm to freely give opinions about good and bad features of the software being used and tasks being performed.

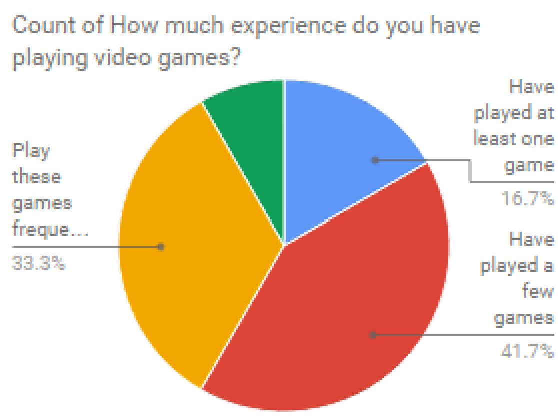
In addition, participants were selected so that they did not all have experience with robots. The resulting participants had the following demographics. All participants were students between the ages of 18 to 29 with normal or corrected-to-normal vision. One participant had marginal experience (between one and ten times) with first response or disaster response incidents, while all other participants had no experience. All other participant demographics are displayed in the pie charts below.

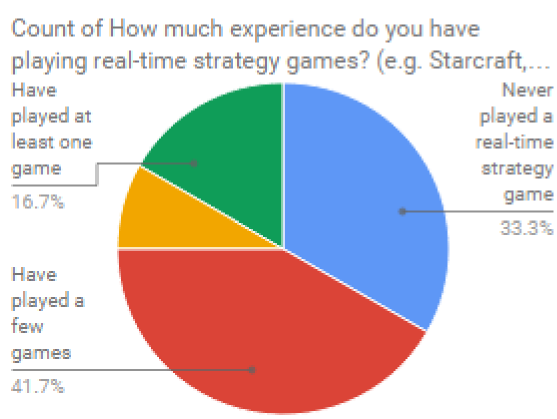


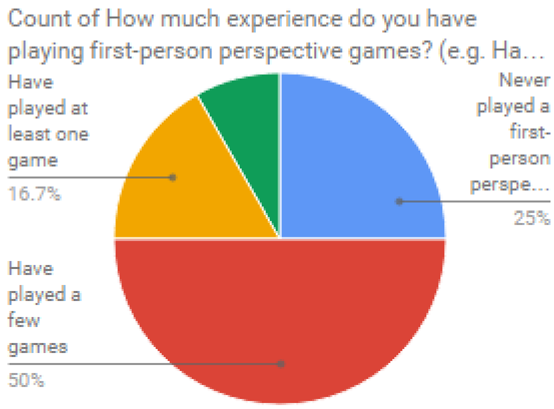












B. Experimental Design

The design of the experiment was a within-subjects and counter-balanced design. Each of the twelve participants sat for two trials, the RVA and a Baseline Visualizaton Algorithm, the BVA, on a map-based interface. The first trial was chosen randomly; six participants sat for the RVA first and six participants sat for the BVA first. The independent variables are as follows:

- Absence or presence of the RVA to control the display of robots on the map
- Participant demographics

The dependent variables are as follows:

- Quantitative measures:
  - The accuracy of a participant when answering questions regarding events on the map and the actions of the robots. This is an objective measure.
  - The participants understanding of the overall situation after the end of each trial, possibly through the use of mouse-over and hover events. This is a subjective measure.
  - The participants' cognitive workload at the end of each trial. This is a subjective measure.
  - The participants preference for the visualization strategy of the robots. This is a subjective measure.
- Qualitative measures:
  - The participants reasoning and justifications for their preference of visualization strategy of the robots. This is a subjective measure.

The data was collected as follows. Demographic information on participants was collected using a questionnaire before the start of both trails. During each trial, the participant would be prompted with 20 decision questions at specific points in time. This helped gauge the accuracy of a participant when answering questions regarding events on the map and the actions of the robots. After each trial, the participant would be prompted to fill in two questionnaires. The first questionnaire was a three dimensional Situational Awareness Rating Technique (3D-SART) questionnaire that measured the participants' understanding of the overall situation on a Likert-type scale with seven values (1 is very low and 7 is very high). Participants were asked to rate ”Demand on Attentional Resources”, ”Supply of Attentional Resources”, ”Understanding the Situation”, and ”Overall Situational Awareness”, given an explanation of each of the terms.The second questionnaire was a NASA Task Load Index (NASA-TLX) questionnaire, a subjective workload assessment tool that computes a workload score based on the weighted averages of six subscales, Mental Demands, Physical Demands, Temporal Demands, Performance, Effort and Frustration. These six values were rated on a Likert-type scale ranging from 0 to 100, where 0 was very low and 100 was very high. Participants were then asked to select the more impactful factor in fifteen pairwise comparisons. Descriptions of each term were given alongside the comparisons. These two trials were then used to compute a TLX score.

C. Hypotheses

Based on the dependent variables shown above, four hypotheses were made. Firstly, the accuracy of a participant when answering questions regarding events on the map and the actions of the robots would be significantly higher for the RVA than for the BVA. Secondly, the participants' understanding of the overall situation after the end of the trial would be significantly better for the RVA than for the BVA. Thirdly, the participants' cognitive workload at the end of each trial would be significantly less for the RVA than for the BVA. Lastly, the participants would prefer the RVA compared to the BVA.

D. Apparatus

The interface was tested for two conditions: the absence or presence of the RVA to control the display of robots on the map. Given the number of participants, it was assumed that there was no significant correlation between the demographics of participants and their results.

The experiment was run as follows. All information given to the participant was read by the experiment administrator from a script. The participant was also free to ask questions at any time, The participant would first fill out an informed consent form, followed by a demographic questionnaire. The participant's first trial would be chosen randomly from one of the RVA or the BVA. The participant would then be given a handout corresponding to the first trial that would introduce the scenario as well as the information items that would appear on the map. After this, the participant would be shown a short demonstration of the map-based interface. Next, the participant would sit for a seven-minute trial, during which the administrator would ask prompt the participant with twenty questions about the situation. The participant only needed to reply to each prompt as quickly and accurately as possible with a ”Yes” or a ”No”. After the trial, the participant would complete two questionnaires, the 3D-SART and the NASA-TLX. Then, the participant would complete the second trial in a similar manner, with a slightly different handout and demonstration beforehand, and the same two questionnaires afterwards. The experiment would conclude with a questionnaire comparing the two visualization strategies of the robots, with an encouragement to provide comments and

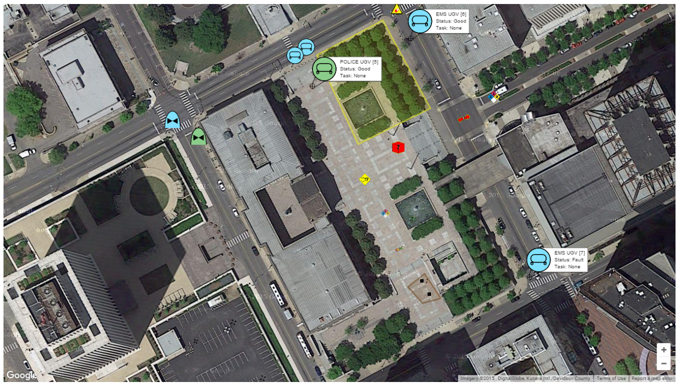


Fig. 2. The RVA in action.

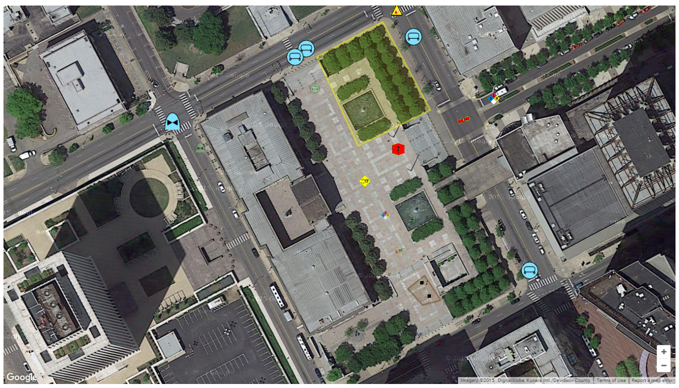


Fig. 3. The BVA in action. Note the difference in visual states in some of the robots on screen.

explanations. Each question in the questionnaire allowed for exactly two options, the RVA for the BVA.

The experiment was run at the same location for each participant. The map-based interface was also consistently displayed on the same laptop to control for screen size and processing power. The entire experiment took about forty minutes on average. A demonstration of the RVA and BVA in action is shown in Figure 2 and Figure 3 respectively at the same point in time.

IV. Results

All statistical analysis of quantitative data were done using non-parametric statistics for the data due to the small sample size.

There was one objective measure, the accuracy of a participant when answering questions regarding events on the map and the actions of the robots. In general, participants using the RVA answered more questions correctly than participants using the BVA ($\mu_{BVA} = 0.5938, \sigma_{BVA} = 0.2298, \mu_{RVA} = 0.6125, \sigma_{RVA} = 0.2230$). However, this result was not found to be significant (p=0.3809 using a Wilcoxon rank-sum test).

There were three subjective measures. The first was the participants' understanding of the overall situation at the end of each trial, measured using the 3D-SART questionnaire. A higher 3D-SART score meant that a participant was more

Criteria	BVA	RVA
Least cognitive workload	1	11
Easiest to understand	2	10
Most easily identify my team's robots	4	8
Most easily understand what my teams robots were doing	2	10
Preferred	1	11

Fig. 4. A count of the number of participant's votes that best satisfied a given criteria.

situationally aware. In general, participants using the RVA had a higher situational awareness than participants using the BVA ($\mu_{BVA} = 3.5, \sigma_{BVA} = 1.679, \mu_{RVA} = 4.667, \sigma_{RVA} = 1.826$). However, this result was not found to be significant (p=0.07436 using Wilcoxon signed-rank test), although it was very close to being significant.

The second was the participants' cognitive workload at the end of each trial, measured using the NASA-TLX. A higher TLX score meant that a participant was subject to a higher cognitive workload. In general, participants using the BVA had a higher TLX score than participants using the RVA ($\mu_{BVA} = 44.69, \sigma_{BVA} = 20.89, \mu_{RVA} = 28.48, \sigma_{RVA} = 20.31$). This result was found to be significant ($p<0.005$ using a Wilcoxon signed-rank test).

The third was the participants' preference for the visualization strategy of the robots, measured using the final questionnaire. Each participant chose a single visualization strategy that best satisfied the given criteria. The results are displayed in the table in Figure 4.

V. Discussion

Given the results above, it was observed that hypotheses three and four were satisfied. In general, the RVA helped to significantly reduce cognitive workload. Furthermore, most participants preferred the RVA over the BVA. The single participant who preferred the BVA noted that the BVA was run second, so the participant was more comfortable with the system during the second trial. The participant also noted that the simplicity of the BVA made it easier to focus on the relevant information as needed. This suggests several possibilities. Participants might need more time to familiarize themselves with the interface, or simply a better demonstration. This result might also suggest that the BVA is preferable to the RVA if the map has low information density. The statistical significance of these results suggests that they would generalize well to larger sample sizes.

Although the RVA performed better than the BVA in hypothesis one and two, the RVA did not perform statistically significantly better given the sample size. This suggests that a larger sample size might be able to clarify the hypotheses. Several participants also commented that due to the size of the Detailed visual state in the RVA, combined with the fact that participants were unable to manually decrease the visual score, the RVA occasionally made for a more cluttered interface. While the RVA improved answer accuracies in general, the increase in clutter may have balanced out the improvement from reduced cognitive workload. Since these results are not statistically significant, it is difficult to tell whether they would generalize to larger sample sizes.

One recurring comment from participants regarding the RVA was that the increase in visual state when a robot required operator input (i.e. a fault occurred or neglect time expired) significantly aided participants in paying attention to that event. Participants that preferred the BVA for several tasks noted that the increase in visual state of robots on the other team obscured their focus on robots that were in their team.

These results suggest that the RVA could be improved by incorporating elements from the BVA. In particular, the participant should have the ability to decrease a robot's visual score at will. One participant found the delay in hover time mildly annoying, suggesting a higher scalar constant corresponding to the [Hover time] component. The increase in visual state of out-team robots might also be augmented with a lower scalar constant so that it does not immediately attract the user's attention.

VI. Conclusion

We have shown that by design, the RVA significantly reduces cognitive workload. Furthermore, the RVA generally led to a better outcome in all metrics, and especially so for the subjective metrics. However, many of the hypotheses that we had anticipated to be true turned out to be statistically insignificant. Even though the RVA was designed to be better than the BVA in all respects, the simplicity of the BVA trumped the RVA in some respects.

The observations above suggest that map-based interfaces require a good balance of user control and usability. The RVA could have been improved simply by providing a method to decrease a robot's visual score. Further, no participants mentioned the selection of discrete visual state, in comparison to some continuous change in size, a mechanism that the authors have themselves considered. This suggests that while interface designers should incorporate a good balance of user control and usability, user testing is of equal, if not greater, importance.

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