Teleoperation of Domestic Service Robots: Effects of Global 3D Environment Maps in the User Interface on Operators' Cognitive and Performance Metrics

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Abstract. This paper investigates the suitability of visualizing global 3D environment maps generated from RGB-D sensor data in teleoperation user interfaces for service robots. We carried out a controlled experiment involving 27 participants, four teleoperation tasks, and two types of novel global 3D mapping techniques. Results show substantial advantages of global 3D mapping over a control condition for three of the four tasks. Global 3D mapping in the user interface lead to reduced search times for objects and to fewer collisions. In most situations it also resulted in less operator workload, higher situation awareness, and higher accuracy of operators' mental models of the remote environment.

Keywords: global environment map, service robot, teleoperation, user interface

1 Introduction

Service robots may assist people in the home in the future. Frail elderly people and people with disabilities may particularly benefit from such robots. However, there are still numerous technical challenges associated with building reliable autonomous robots for unstructured environments. For example, robots can fail to find navigation paths through narrow passages or objects to be fetched can fail to be detected in cluttered scenes or under low illumination. Semi-autonomous robots [1] may be a viable shorter-term solution: when a robot cannot complete a task, a remote human operator takes control and tries to solve the local problem. The design of suitable teleoperation user interfaces therefore remains an important subject of research.

Studies have shown that user interfaces merely relying on the visualization of a video stream from a camera on the robot and a floor map lead to high collision rates [2], long task completion times [3, 2], high operator workload [4], and low situation awareness [5]. The camera's narrow field of view prevents operators from acquiring environmental cues from the surrounding. Also, people form mental models of spatial environments and rely on them for spatial reasoning [6]. In video-centric interfaces, operators need to infer a spatial mental model from two-dimensional data, which may result in less accurate models and negatively affect performance.

It has thus been established that teleoperators need more comprehensive information on the robot's environment to be able to control it effectively. Visualizing data from various sensors in separate areas of the screen has however shown to be problematic with regard to operators' task performance and cognitive load [2, 4]. To avoid divided attention and information overload, sensor fusion, augmentation, and ecological interfaces, where data from different sensors are integrated with direct spatial reference to the environment, have been proposed [7, 2]. To address the field of view problem, the use of multiple and panospheric cameras has been explored [8]. However, such approaches impose a high load on network bandwidth while not allowing, for example, assessment of distances between objects. Approaches where 2D map and video are enriched with a schematic 3D environment model have shown to lead to improvements in user performance [3, 4] but they require manual modeling of each apartment and can be misleading when environment features have changed.

With the advent of affordable depth sensors, techniques for generating complete 3D representations of the environment have emerged more recently. With infrared sensors, time-of-flight cameras, or 3D laser scanners, the robot acquires 3D data while moving around. Algorithms generate, and update in real-time, a global 3D environment map in form of a voxel-based point cloud [9, 10] or a set of geometric primitives [11, 12]. Research on global 3D environment mapping has so far focused on algorithms and applications in autonomous reasoning [9-12]. In this paper, we examine the suitability of displaying global 3D environment maps during teleoperation. The maps provide a teleoperator with recent and detailed information on objects all around the robot, on environment features further away, and on distances between objects.

2 User Interface, Robot, and Mapping Techniques

The user interface employed in this study (Figs. 1 and 2) was developed as part of a wider semi-autonomous human-robot interaction framework for assisting elderly people in the home in an iterative user-centered design process involving studies with a total of 241 participants [1]. The user interface's main intended user group is teleassistance staff but we do not regard its use limited to professional applications. The user interface is integrated with the Care-O-bot 3 service robot [13] (Fig. 2). Care-O-bot 3 has an omni-directional base, three laser range finders, and a Kinect RGB-D camera. During teleoperation, the robot autonomously avoids obstacles of up to 40cm above ground based on 2D laser range data but not currently higher objects.

The user interface is based on RViz as part of ROS (Robot Operating System) Electric [15]. Following the idea of ecological interfaces [2], it offers the following elements visualized in a unified way in a single 3D scene (Figs. 1 and 2): (1) laser-based 2D floor map (grey/black), (2) laser-based historic obstacle map (purple, active in Fig. 2 only), (3) live laser data (red), (4) live 3D colored point cloud in the robot's field of view, (5) global 3D environment map (voxel-based or geometric), (6) robot in accurate size and shape, (7) collision-relevant safety area around the robot ("footprint”, yellow, Fig. 2), (8) a sectioned band of collision indicators around the robot lighting up when the robot slows down on approaching an obstacle or movement in a direction is not possible (not shown in Figs. 1 and 2). As a ninth element, a video image is overlaid. Users can freely rotate, pan, and zoom the 3D scene using the mouse. Navigation of the mobile platform is realized with the SpaceNavigator 3D mouse [14] in the coordinate system of the operator‘s current viewpoint on the scene.

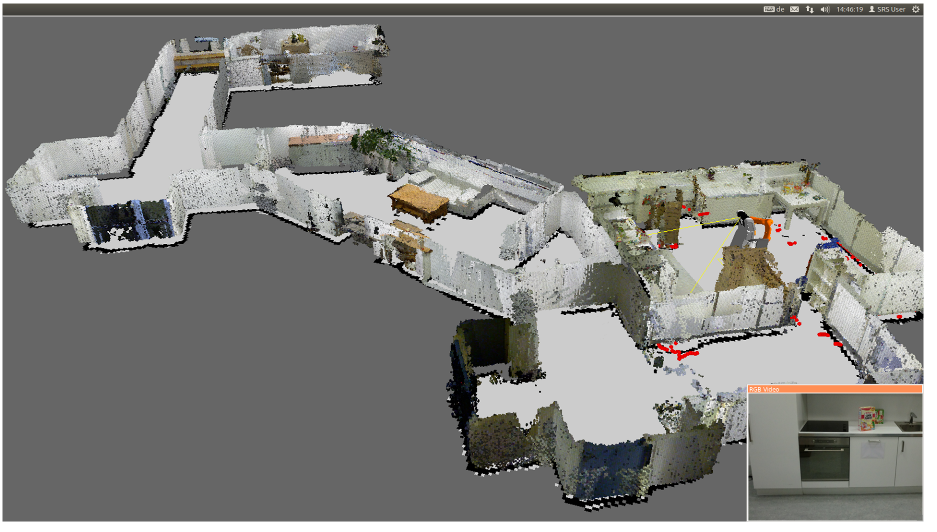

Fig. 1. User interface in zoomed-out perspective with apartment-sized environment mapped using voxel-based mapping technique

Two types of global 3D mapping techniques have been implemented. The voxel-based technique is based on OctoMap [9], a probabilistic approach that uses octrees to represent 3D occupancy grids. The geometric 3D mapping technique [11] segments consecutive point clouds into homogeneous regions, derives geometric primitives like planes or cylinders, and merges them into a map. From a technical point of view, its main advantages over the voxel-based technique are lower network bandwidth consumption and less required client-side computational resources for display.

3 Research Questions

We assumed that, due to the complete 3D representation of the environment, global 3D environment maps in the user interface should usually lead to improved user performance, decreased workload, increased situation awareness, and more accurate mental models of the remote environment. On the other hand, it is conceivable that they might not be needed in some situations or even be disadvantageous. For example, the visualization of a global 3D map might negatively impact user performance because close objects can obstruct the view on task-relevant objects behind them or lead to higher cognitive load due to additional interpretation effort. Concerning the suitability of voxel-based versus geometric mapping, likewise, arguments for differences in both directions are feasible. For example, the more simplistic, reduced visualization of the environment with a geometric approach might reduce required interpretation efforts. On the other hand, the algorithmic processing of the point cloud necessarily introduces artifacts that might be confusing.

Due to a wide range of factors that might affect results and a lack of directly comparable studies in the literature, we adopted an exploratory attitude towards this research. Our main goal was to identify usage scenarios where global 3D environment maps in the remote user interface would be advantageous as well as scenarios where this would rather not be the case. We were further interested in potential differences in the suitability of voxel-based versus geometric mapping approaches.

4 Method

Research Design. We adopted a between-subjects experimental design with three conditions: control condition without global 3D environment mapping (C), voxel-based global 3D mapping condition (V), geometric global 3D mapping condition (G). The user interface did not differ between conditions other than in the type (or absence) of global 3D environment mapping. All other visualization elements described in Section 2 were available in all conditions.

Participants. 27 people participated in the experiment (9 in each group). Their age ranged from 19 to 41 years (mean age group C: 27.4; V: 23.4; G: 26.7). All participants were male to avoid a confounding effect due to known gender differences in spatial problem solving [19]. Participants had no previous experience with robots, teleoperation user interfaces, or 3D mice. They used computers at least 12 hours per week but played 3D games or used professional 3D applications only up to 2 hours per week (mean 3D usage hours C: 0.5; V: 0.6; G: 0.5). All but two participants had university degrees or were currently pursuing such. Participants received €30 of compensation. Participants underwent a spatial ability test (abbr. Vandenberg Mental Rotations Test) [20] and were assigned to experimental conditions based on their score in a balanced way (mean score C: 4.4 out of 6; V: 4.3; G: 4.6). Participants also underwent a Snellen visual acuity test and all achieved a score of 5 or higher (mean score C: 6.7; V: 7.2; G: 6.1). According to a further color vision test, one participant in each group did not have full color vision.

Metrics. We employed objective and subjective metrics to investigate several constructs. Metrics mainly relating to performance were: time to complete the task, length of the path the robot traveled, and robot rotation. We assessed perceived workload with the NASA Task Load Index (TLX) in its unweighted (raw) form [16] post-task. We further measured perceived situation awareness post-task with the three-dimensional Situation Awareness Rating Technique (SART) [17]. We adjusted the SART scale to a range from 0 to 100. To assess perceived quality of the mental model of the remote environment, we employed (6) the subscale "spatial situation model"

(SSM) from the Spatial Presence Questionnaire MEC-SPQ [18] post-experiment. For applicable tasks, we also asked participants to recall the number of obstacles around the robot as an indicator of the accuracy of their spatial mental model. For one task, we further recorded the number of collisions as a performance metric and an implicit indicator of situation awareness.

Procedure. The experiment took place in three rooms connected by two corridors. We installed 80 household furniture items and objects to simulate a home environment with a kitchen, a living room, and a bedroom. To control for illumination we covered all windows and used interior lighting only. Participants operated the robot from a separate fourth room and did not see the robot or its environment until after the trials.

After initial spatial ability and vision tests, participants underwent a 45-min training on robot hardware and sensors, user interface concept and visualization elements, SpaceNavigator device, teleoperation (in simulation). The type of global mapping visualized during training corresponded to the participants' experimental condition. Participants then carried out four teleoperation tasks (Fig. 2) with the real robot and filled in a questionnaire after each task. The tasks were designed to cover a range of different scenarios. At the beginning of each task, participants were confronted with a problem of the robot and asked to solve it quickly but without becoming stressed or sacrificing accuracy. The room's global map was always up to date, assuming the robot had moved around prior to contacting the teleoperator for assistance.

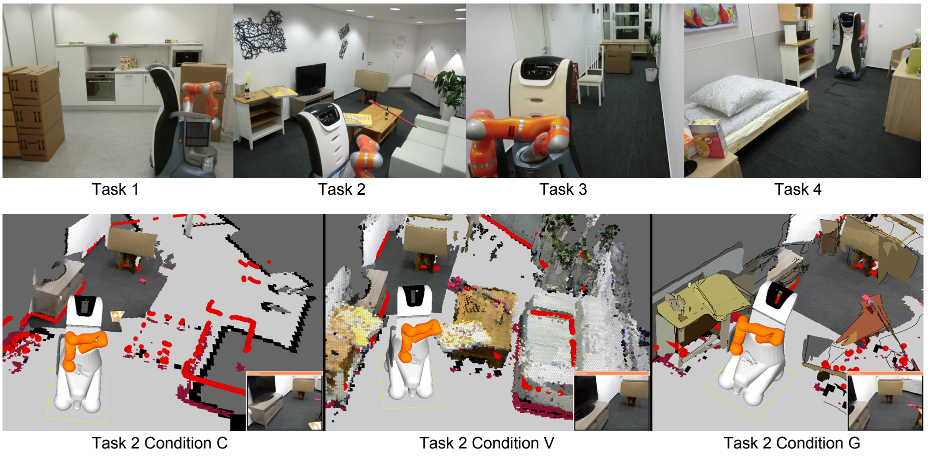

Fig. 2. Overview of the task setups with robot at starting positions (upper row); robot during task 2 at similar positions in the three experimental conditions (lower row)

Task 1: For this task in the kitchen only, we simulated darkness, so no video and only grayscale live depth data were available. The global maps were generated while the room was still illuminated. The robot's problem was that it could not find a medicine package to be fetched. The participant was told that the local elderly user stated to have left the package on the chair in the kitchen. The goal was to find the chair (which was hidden in a corner and there were three such corners) and approach it.

Task 2: This task took place in the living room. The robot's problem was that it could not find a navigation path to its destination due to a narrow passage. Participants were asked to navigate the robot to the other side of the room. There were elevated protruding obstacles so it was possible for the robot to collide. Participants were asked to make the robot pass without collisions.

Task 3: This task took place in the corridor and the robot's problem was that it could not find a navigation path to the bedroom. All obstacles were on the floor. Towards the end of the task, participants had to push aside a carton with the robot.

Task 4: This task took place in the bedroom. As in task 1, participants had to find an object but it was small and without a characteristic shape (a rectangular pack of tea bags). The room was cluttered with objects and there were five possible hiding places.

After the last task, the session was recapitulated, participants were interviewed on their impressions, and then completed the post-experiment questions.

Data Analysis. We performed pairwise group comparisons using two-tailed independent samples *t*-tests, assuming normal distribution. For the collision metric only we used a two-tailed Wald test, assuming Poisson distribution. We used robust estimation of variance (Huber-White sandwich). Due to the exploratory nature of the experiment we did not adjust for multiple testing [21].

5 Results

All participants were able to complete all tasks, indicating effectiveness in all experimental conditions. Results on the investigated metrics are described subsequently.

Task 1: Finding a Large Object. As shown in Table 1, participants in both global map conditions were able to find the target object (chair) significantly faster with much shorter path lengths and less required robot rotation than in the control condition. They also experienced significantly lower workload and were subjectively more aware of the situation in conditions V and G. There was a tendency for condition V to be somewhat more efficient than condition G but statistical significance is only reached for the path length metric.

Task 2: Navigating Around Elevated Obstacles. Results in Table 2 show that task 2 was completed the fastest in the control condition. The difference to both, conditions V and G is statistically significant. Perceived workload was highest in condition G and the difference is significant over conditions C and V. In condition C, object collisions were most frequent and participants recalled significantly less obstacles than in the global map conditions. No significant differences were found for path lengths, robot rotation, perceived situation awareness.

Task 3: Navigating Around Obstacles on the Floor. Results for task 3 (Table 3) show no significant differences between conditions. There was a tendency to report more obstacles in condition V than in conditions G and C.

Task 4: Finding a Small Object. As shown in Table 4, participants in condition V found the pack of tea bags the fastest, with shortest path lengths, least rotation, and least cognitive load, statistically significant over conditions C and G. Perceived situation awareness was highest in condition V with a significant difference over C but just as a tendency over G. There was a tendency for better suitability of condition G than C for this task but the differences are not statistically significant.

Spatial Situation Model. Results of the post-experiment MEC-SPQ SSM subscale (Table 5) show that participants rated the perceived quality of their mental model of the situation significantly higher in condition V than in conditions C and G.

Table 1. Results of task 1 (conditions: C - control; V - voxel map; G - geometric map)

Metric	Means with 95% confidence intervals	Difference betw. means	
Task completion time	C: 235s	C vs. V:	p = 0.001 **
	V: 109s	C vs. G:	p = 0.004 **
	G: 126s	V vs. G:	p = 0.376
Robot path length	C: 8.4m	C vs. V:	p = 0.001 **
	V: 3.1m	C vs. G:	p = 0.004 **
	G: 4.2m	V vs. G:	p = 0.031 *
Robot rotation	C: 2.5rev	C vs. V:	p = 0.000 **
	V: 0.6rev	C vs. G:	p = 0.000 **
	G: 0.8rev	V vs. G:	p = 0.542
Perceived workload	C: 40.4	C vs. V:	p = 0.002 **
(NASA-TLX raw)	V: 16.8	C vs. G:	p = 0.029 *
Scale: 0-100	G: 23.1	V vs. G:	p = 0.115
Perceived situation	C: 55.9	C vs. V:	p = 0.017 *
awareness (SART)	V: 72.0	C vs. G:	p = 0.011 *
Scale: 0-100	G: 72.9	V vs. G:	p = 0.885

Table 2. Results of task 2 (conditions: C - control; V - voxel map; G - geometric map)

Metric	Means with 95% confidence intervals	Difference betw. means	
Task completion time	C: 121s	C vs. V:	p = 0.029 *
	V: 171s	C vs. G:	p = 0.001 **
	G: 206s	V vs. G:	p = 0.154
Robot path length	C: 5.6m	C vs. V:	p = 0.405
	V: 5.5m	C vs. G:	p = 0.406
	G: 5.4m	V vs. G:	p = 0.126
Robot rotation	C: 0.6rev	C vs. V:	p = 0.579
	V: 0.7rev	C vs. G:	p = 0.118
	G: 0.8rev	V vs. G:	p = 0.182
Perceived workload	C: 36.8	C vs. V:	p = 0.754
(NASA-TLX raw)	V: 34.9	C vs. G:	p = 0.010 *
Scale: 0-100	G: 52.0	V vs. G:	p = 0.003 **
Perceived situation	C: 53.1	C vs. V:	p = 0.331
awareness (SART)	V: 59.3	C vs. G:	p = 0.483
Scale: 0-100	G: 49.1	V vs. G:	p = 0.156
Object collisions	C: 1.7	C vs. V:	p = 0.044 *
	V: 0.6	C vs. G:	p = 0.013 *
	G: 0.9	V vs. G:	p = 0.352
Obstacles recalled	C: 2.1	C vs. V:	p = 0.001 **
	V: 3.3	C vs. G:	p = 0.001 **
	G: 3.4	V vs. G:	p = 0.771

Table 3. Results of task 3 (conditions: C - control; V - voxel map; G - geometric map)

Metric	Means with 95% confidence intervals	Difference betw. means	
Task completion time	C: 139s	C vs. V:	p = 0.333
	V: 155s	C vs. G:	p = 0.195
	G: 160s	V vs. G:	p = 0.722
Robot path length	C: 6.1m	C vs. V:	p = 0.780
	V: 6.0m	C vs. G:	p = 0.902
	G: 6.1m	V vs. G:	p = 0.834
Robot rotation	C: 0.6rev	C vs. V:	p = 0.689
	V: 0.6rev	C vs. G:	p = 0.545
	G: 0.6rev	V vs. G:	p = 0.846
Perceived workload	C: 37.1	C vs. V:	p = 0.230
(NASA-TLX raw)	V: 30.9	C vs. G:	p = 0.515
Scale: 0-100	G: 33.2	V vs. G:	p = 0.737
Perceived situation	C: 60.7	C vs. V:	p = 0.493
awareness (SART)	V: 65.3	C vs. G:	p = 0.817
Scale: 0-100	G: 62.0	V vs. G:	p = 0.636
Obstacles recalled	C: 2.9	C vs. V:	p = 0.264
	V: 3.3	C vs. G:	p = 0.748
	G: 2.8	V vs. G:	p = 0.057

Table 4. Results of task 4 (conditions: C - control; V - voxel map; G - geometric map)

Metric	Means with 95% confidence intervals	Difference betw. means	
Task completion time	C: 215s	C vs. V:	p = 0.001 **
	V: 97s	C vs. G:	p = 0.317
	G: 174s	V vs. G:	p = 0.014 *
Robot path length	C: 5.9m	C vs. V:	p = 0.020 *
	V: 2.8m	C vs. G:	p = 0.147
	G: 4.0m	V vs. G:	p = 0.020 *
Robot rotation	C: 2.2rev	C vs. V:	p = 0.013 *
	V: 1.2rev	C vs. G:	p = 0.518
	G: 2.0rev	V vs. G:	p = 0.018 *
Perceived workload	C: 42.5	C vs. V:	p = 0.017 *
(NASA-TLX raw)	V: 21.6	C vs. G:	p = 0.547
Scale: 0-100	G: 36.9	V vs. G:	p = 0.021 *
Perceived situation	C: 55.8	C vs. V:	p = 0.029 *
awareness (SART)	V: 72.8	C vs. G:	p = 0.514
Scale: 0-100	G: 60.1	V vs. G:	p = 0.133

Table 5. Results of MEC-SPQ SSM (conditions: C - control; V - voxel map; G - geometric map)

Metric	Means with 95% confidence intervals	Difference betw. means	
Perceived quality of	C: 3.6	C vs. V:	p = 0.006 **
spatial situation model	V: 4.3	C vs. G:	p = 0.190
5-point scale	G: 3.9	V vs. G:	p = 0.031 *

6 Discussion

When searching for a large object, there were strong benefits of using either type of global 3D map, voxel-based or geometric. Participants were around twice as fast in the mapping-enabled conditions than in the control condition when navigating the robot to the hidden chair in task 1. They also experienced less cognitive load and higher situation awareness. When searching for a smaller object (task 4), benefits were only clear in case of the voxel-based mapping approach. Likely, due to the more schematic and coarse environment representation in the geometric map, operators could not obtain a direct cue as to the target object's location. There still was some non-significant tendency for benefits of using the geometric map over not using a 3D map. Perhaps operators had better overall orientation than without a global 3D map.

When navigating around obstacles, benefits of using global 3D maps were only apparent for task 2, where obstacles were elevated. Interestingly, users in the control condition accomplished this task the fastest. However, they also had the highest number of collisions (C: 1.7, V: 0.6, G: 0.9 collisions on average). It seems that operators rushed through the obstacle course unaware of the existence or proximity to obstacles. This is corroborated by the fact that substantially too few obstacles were recalled in the control condition. A further interesting result for task 2 is that operators using the geometric map experienced higher workload than in the two other conditions. For other tasks too, there was a tendency for higher workload in the geometric condition than in the voxel condition. Perhaps this can be attributed to some ambiguity in visualization due to artifacts of algorithmic processing compared to the more unprocessed representation in a voxel map. The fact that results for all metrics were similar for task 3 suggests that this might be a scenario without benefits of using global 3D mapping. A likely reason is that all obstacles were on the floor and thus well visible through laser scanner visualization in the control condition too.

Participants using voxel-based maps rated the quality of their mental model of the remote environment highest on average. Results on the recall metric further suggest that whether or not 3D mapping leads to more accurate mental models may also depend on the environment or task. For task 2, participants in both mapping-enabled conditions were clearly much more accurate in recalling obstacles (C: 2.1, V: 3.3, G: 3.4 recalled; correct: 4). In task 3, where all obstacles were on the floor, no significant differences were found. Results thus suggest that global 3D maps tend to support the formation of accurate mental models but need not necessarily in every situation.

To summarize, visualizing global 3D environment maps in the teleoperation user interface in most situations showed to have positive effects on user performance, workload, situation awareness, and accuracy of users' spatial mental models. It substantially reduced search times for objects and reduced collisions when navigating around elevated obstacles. On a broad level, our results corroborate the findings of earlier studies on the benefits of 3D-enhanced teleoperation user interfaces [2, 3]. The automated, sensor-based, and fully three-dimensional mapping techniques evaluated in this paper can be regarded an evolution of those earlier approaches. Benefits of the voxel-based mapping technique were overall more pronounced than of the geometric mapping technique but the geometric mapping technique tended to show benefits over the control condition too. Due to its technical advantages, geometric mapping should be considered especially when identifying fine detail in the environment is not crucial.

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