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Level of detail in visualization for human autonomy teaming: Speed, accuracy, and workload effects

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Abstract

For human autonomy teaming, information for promoting transparency could lead to information overload, negatively impacting performance and workload. This paper presents an empirical study investigating how different level of details (LODs) about the autonomy represented on the user interface would influence speed, accuracy, and workload. Specifically, we compared visualizations of a lost person model at four different LODs to aid in directing human and unmanned aerial vehicles searchers in search and rescue missions. The lowest LOD was found to support higher accuracy but at the expense of speed. The highest LOD induced the highest workload, while the other three LODs induced lower and similar levels of workload. The results indicate that the LOD in transparent displays could induce a speed and accuracy tradeoff.

Keywords

Human autonomy teaming, level of detail, transparency, search and rescue

Introduction

Human and autonomous agents must work as a team to take advantage of their respective capabilities to accomplish complex tasks (Lyons et al., 2021; McNeese et al., 2018; Shively et al., 2018). The collaboration between humans and autonomy is commonly referred to as human autonomy teaming (HAT). Though essential, the collaboration between human and autonomous agents often requires extensive efforts in interacting with one another, expressing thoughts, monitoring others, attending to immediate tasks, and establishing common ground that could induce cognitive load and consume time (Kolfschoten & Brazier, 2013). Complex tasks also demand that human and autonomous agents must have shared activity, joint intention, common ground, and intended goals (Hoffman & Breazeal, 2004). Thus, HAT requires human to have a good understanding and prediction of the actions by autonomy (Endsley, 2017).

In HAT, transparency, specifically transparent displays, has been commonly proposed to be the solution for facilitating the understanding of autonomy. Transparency refers to "the descriptive quality of an interface about its abilities to afford an operator's comprehension about an intelligent agent's intent, performance, plans, and reasoning process" (J. Y. Chen et al., 2014, p. 2). Koo et al. (2015) found that providing drivers with situational information explaining the reason for autonomous agents' reactions before taking action could promote acceptance in semi-autonomous driving tasks. In multi-unmanned vehicle management, Mercado et al. (2016) found that a display with projection information, reasoning and rationale of the agent in path recommendation offered better usability than a display with only basic path information. Stowers et al. (2020) found higher acceptance rate of correct recommendations with the display presenting perception, comprehension, and projection about states of autonomy along with uncertainty information than with displays presenting just perception and comprehension. For a helicopter operator managing multiple unmanned aerial vehicles (UAVs) in simulation, Roth et al. (2020) found response time reduced when using a transparent display with critical information and future information than using the one with only currently adopted actions. Zhang et al. (2020) found that showing confidence scores in AI-assisted decision-making could facilitate appropriate trust for applying people's knowledge to improve decision outcomes in prediction tasks. Kraus et al. (2020) found that providing information on the ambiguous sensor information caused by reflections and glares and consequences due to malfunctions

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of a level 3 automated vehicle prior to driving could avoid the decline of trust.

However, indiscriminate inclusion of information about autonomy may overwhelm human information processing (Moacdieh & Sarter, 2015). It is not practical for a human to perceive and analyze all information about the autonomous agents given the time, accuracy, and quality constraints (Westin et al., 2016). Moreover, important information could be buried by a large amount of less useful information resulting in a transparency paradox (Stohl et al., 2016).

Transparent displays with too much information may demand more cognitive effort to process the information and hinder performance. Stowers et al. (2016) found that with additional uncertainty information displayed in texts, the proportion of correct response increased, but the usability of the user interface decreased. In a follow-up study, Stowers et al. (2020) found that additional uncertainty information displayed in texts increased acceptance rate of correct recommendations but decreased response time. Skraaning and Jamieson (2021) found that, in the context of operating an automated power plant system, transparent displays for operating components (e.g., controllers, protections) improved response time, overall task performance, and workload; whereas for operating plant-wide functions, the transparent display could lead to decreased performance and increased workload. Helldin et al. (2013) found that the presence of uncertainty information about the autonomy in the user interface induced the highest trust ratings but the longest classification time for pilots to classify friendly versus enemy aircraft. Guznov et al. (2020) found workload increased with more detaled information delivered in text messages for promoting transparent communication when humans monitor and intervene in an autonomous robot to avoid collisions during navigation. For routing UAV through hazardous areas requiring occasional operator engagement, T. Chen et al. (2014) found that a display containing a medium amount of information on system status yielded the lowest workload compared to a display with the most information on raw data from system components and a display with the least information only about general representation of the system status. Thus, information postulated to promote a better understanding of autonomy may result in unintended effects on performance and workload depending on contexts.

Empirical studies focusing on transparent displays have revealed that the inclusion of information regarding autonomy on displays can have intricate effects on usability, workload, and performance. However, drawing a definitive conclusion regarding the optimal quantity of autonomy-related information is challenging due to variations in the types of information presented across different transparent displays in these studies, rather than variations in the amount of information within a single type. Therefore, further research is required to determine the suitable level of detail (LOD) for specific types of information, as well as the overall quantity of information pertaining to autonomy. To address this research gap, we investigated the effects of visualization of a lost person model (LPM) at different LODs on speed, accuracy, and workload in the context of search and rescue (SAR).

LOD represents the amount of information aggregated or organized in communication for the human to perceive, comprehend, and respond to autonomy. Ideally, LOD should be objective and measurable to establish quantitative relationships of LOD with usability, workload, and performance. High LOD delivers less information so that users can easily acquire an overview of a specific aspect or feature of autonomy. In contrast, low LOD delivers more information so that users can access the details on a specific aspect of autonomy, such as raw data or the decision mechanisms.

Lost person modeling (LPM) computes the probability of lost person for a given location and probability of area based on the probable movements given the behavioral profile of the lost persons, and environmental conditions, such as distance, weather, and elevation (Koester, 2008; Mansfield et al., 2020). Given typical sizable search area, the search region usually needs to be divided into smaller segments for prioritizing and assigning search teams given resource constraints (Hill, 2012).

The LPMs could be categorized by statistic based model (such as distance ring model, watershed model), and agent based model. The distance ring model computes radii from IPP for 25%, 50%, 75%, and 95% chance of finding the lost person (Syrotuck, 2000). Doke (2012) developed the watershed model that divides the search area into segments based on ridge lines then incrementally indexed from initial planned point to outside boundarie. Agent-based modeling simulates possible and likely lost-person movement trajectories by randomly selecting movement behaviors from the distribution of known lost person reorientation strategies for the given terrain. Adopting Monte Carlo simulation of moving particles based on behavioral heuristics and environmental elements (Kratzke et al., 2010; Lin & Goodrich, 2010), our research team (Hashimoto & Abaid, 2019) developed an agent-based model, which uses the lost-person profile and environmental parameters captured by Koester (2008) as inputs to define the parameters of lost-person behaviors. The probability map can then be estimated based on the distribution of lost-person location for all simulated trajectories at a given time (Hashimoto et al., 2022).

Wilderness SAR missions are time-critical, sometimes situated in high-risk environments. SAR would benefit from deploying UAVs to reduce the risk of humans traveling to dangerous or difficult-to-access terrains (Jiang et al., 2022; Karaca et al., 2018). With autonomous path planning, human resources (e.g., UAV pilots and sensor operators) can be further relieved (Goodrich et al., 2007). To enhance the efficiency of search, LPMs are used in UAV path planning for SAR (Heintzman et al., 2021). For this reason, SAR professionals need to interpret the LPM results in order to understand the UAV path planner.

Figure 1. SAR web application prototype. Teams were assigned to segments and map tools on the right. The image from UAVs is shown by clicking on the spotted clue.

Our investigation involved an empirical study recruiting participants to assign search teams to different areas with the support of visualizing the LPM at different LODs in simulated SAR missions. We hypothesized that lower LODs would improve the decision-making accuracy of the mission because more information at lower LODs illustrated the modeling mechanism more accurately. However, more information would increase the time and effort for information processing.

Method

Twenty-five students (10M, 15F) were recruited from a major university in southwest Virginia. The average age was 24.90 years (*SD*=5). Seven and eighteen participants were undergraduate and graduate students, respectively. Participants self-reported normal or corrected-to-normal vision.

Experimental Platform

The SAR web application prototype was developed as the experimental platform for this study (Williams et al., 2020). The application was connected to a geographical information system (GIS), specifically ArcGIS, to gather high-quality maps with many different layers of information and built on JavaScript to provide custom user interface features. Critically for this study, this web application supported different visualizations of the agent-based LPM (Hashimoto & Abaid, 2019), automatic segmentation of the search area around IPP, and assignment of search teams to different search segments (Figure 1). The POAs estimated by the LPM are visualized by overlays on the geographic map.

Experimental Design and Manipulation

A within-subjects design was employed to test the single treatment of LOD with four levels – Ring, Weighted map, Heat map, and Trajectory (Table 1 and Figure 2). Based on the amont of information, the four visualizations were classified into four LODs. All the actionable items in the user interface were the same across the four treatment levels.

Procedure

The experiment was conducted over an online meeting software and the SAR web application prototype. Upon joining the online meeting, the participant was first briefed on the experimental procedure, followed by requesting an electronic signature for the online consent form. Then, the participant completed a demographics questionnaire. Participants were provided a training trial, in which the participant could assign teams and explore the user interface. The participant could assign teams for a maximum of five rounds but could complete the scenario prior to this limit. For each round, the participant assigned four search teams to different segments of the search area. The searched segments and the discovered clue would be marked on display. The participant was asked to complete the task with the minimum number of rounds at the fastest speed. The training ended when the participant had no questions about the user interface or the experimental task. After training and a short break, the participants completed four trials, each presented with a different level of LODs (i.e., the four different visualizations). Upon completion of each trial, the participants would fill in the workload questionnaire. All participant interactions with the web application were

Table 1. The visualizations in four LODs.

Visualization	Description
Ring	High LOD, presenting four concentric rings from IPP with 25%, 50%, 75%, and 95% probabilities that the lost person can be located, respectively.
Weighted map	Medium LOD, presenting POAs aggregated by search segments shaded in different color saturation. The information may be most efficient for the task of assigning search teams because the POA for each segment is color coded, although the computational mechanism/model process is not represented.
Heat map	Low LOD, generated with a Gaussian kernel for the entire search area. Unlike weighted map, heat map can highlight variations within a search segment.
Trajectory	The lowest LOD, presenting raw data by lines of the possible moving paths generated by the LPM/Monte Carlo simulation. Thus, the Trajectory visualization indicated how the model computed the POAs, providing more details than the other three visualizations.

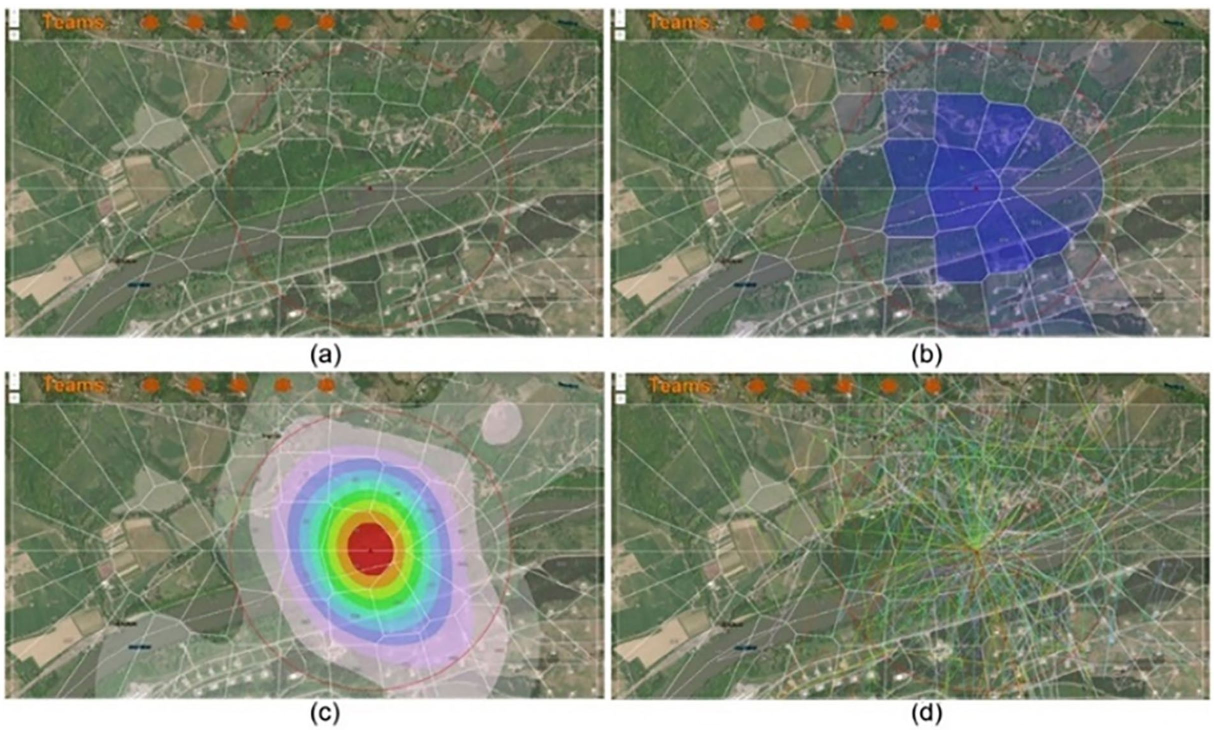

Figure 2. The four treatment levels for the LPM for a SAR mission: a) Ring, b) Weighted map, c) Heat map, d) Trajectory.

logged to compute task performance metrics. The presentation order of the experimental conditions was counterbalanced. The experiment lasted about 1.5 hours.

Measures

Two performance metrics were computed to reflect accuracy and speed in SAR decision-making. *Total rounds* were the number of rounds of assigning teams to segments for locating the lost person. In each scenario trial, participants could have a maximum of five rounds to finish the search task. If the lost person was not located within the limit of five rounds, the total rounds were set to six for scoring. *Duration per assignment round (DPR)* was the time to assign the four teams to segments in one round.

Workload scores were the averaged ratings across six NASA TLX items, administered after every trial without pairwise comparison (i.e., Raw TLX, Hart, 2006).

Results

Correlations

Spearman's ρ rank-order correlation statistics were used to examine the relationships between workload and task performance. Workload was positively and strongly correlated to

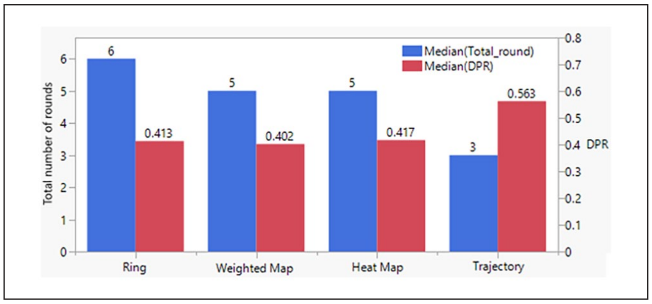

Figure 3. The medians of total number of rounds and DPR of the four LODs.

total rounds of task ($r_s(98) = 0.77, p < .001$), and also positively and moderately correlated to duration per assignment round ($r_s(98) = 0.50, p < .001$). Workload was higher when participants had to perform more rounds and spend more time per round. Correlation between total rounds and duration per round was not significant.

Task performance

A Friedman test revealed a marginal main effect of LOD on total rounds of team assignment to finding the lost person $\left(\chi^2(3, N = 25) = 7.4, p = .06\right)$. Wilcoxon signed-rank tests with a Bonferroni-adjusted alpha of 0.008 (i.e., 0.05/6) were used for post hoc comparison. We consider Bonferroni correction with an alpha of 0.016 (i.e., 0.1/6) as a marginal effect. Participants marginally required fewer total rounds with the Trajectory ($Mdn = 3$) than Ring ($Mdn = 6; Z = -2.43, p = .015$). Other comparisons were not significant.

A Friedman test revealed a main effect of LOD on DPR $\left(\chi^2(3, N = 25) = 10.8, p = .013\right)$. Wilcoxon signed-rank tests with a Bonferroni-adjusted alpha of .008 (i.e., 0.05/6) were used for post hoc comparisons. Participants spent longer time per round of assignments on Trajectory $(Mdn = 0.56)$ than Heat map ($Mdn = 0.42; Z = -2.97, p = .003$), Weighted map ($Mdn = 0.40; Z = -3.32, p < .001$), and Ring ($Mdn = 0.41; Z = -2.70, p = .007$). Figure 3 present the bar graphs of total rounds and DPR, respectively.

Workload

A Friedman test revealed a significant effect of LOD on the overall workload ($\chi^2(3, N = 25) = 8.75, p = .033$). Wilcoxon signed-rank test with a Bonferroni-adjusted alpha level of .008 (i.e., 0.05/6) was used for post hoc comparisons. Ring $(Mdn = 2.67)$ was found to be higher than the Weighted map on workload $(Mdn = 1.83; Z = -2.97, p = .003)$. Figure 4 shows the medians of workload scores.

Discussion

This paper presents the first study explicitly investigating how different LODs about an agent-based LPM could influence

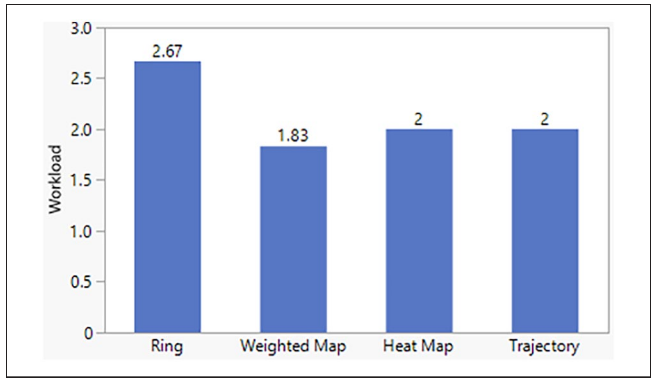

Figure 4. The medians of the workload of the four LODs.

performance and workload for SAR missions. The results indicated that the LODs about LPM influenced performance and workload in a complex manner that does not conform to the simplistic notion that conveying more information about autonomy would improve outcomes.

As LOD decreased, the number of rounds to finding the lost person tended to decrease, whereas the duration per assignment round tended to increase. The number of rounds to completing a mission scenario and DPR represented decision accuracy and speed supported by the visualizations of the LPM at different LODs, respectively. The Trajectory visualization with the lowest LOD facilitated the fewest rounds to completion (i.e., highest accuracy), but this improvement in decision accuracy seemed to incur a cost in decision speed, as the Trajectory visualization resulted in the longest DPR (Figure 3). The results indicate that LODs could induce the speed-accuracy tradeoff (Wickelgren, 1977). At lower LODs, more cognitive resources are needed to process more details or information, thereby increasing the decision time. Stowers et al. (2020) also observed an increase in response time with additional information that facilitated more correct responses to recommendations proposed by an intelligent agent for operating multiple UAVs.

LODs about autonomy exerted a non-linear impact on cognitive workload. Trajectory visualization, Heat map, and Weighted map visualization all induced similar cognitive workload that was lower than the load with the Ring map visualization. This finding suggests that lower LOD about autonomy could reduce the subjective workload of thinking about the rationale of the decisions by the autonomy, irrespective of whether the amount of information is sufficient to support the best performance. A major implication is that LODs of the LPM visualization inducing the lowest workload may not necessarily yield the best performance.

The empirical results contrasting the impacts of different LODs on accuracy, speed, and workload highlight the complexity of designing for HAT. The results did not indicate any one LOD to be universally optimal for all human performance constructs. For example, the lowest LOD or the Trajectory visualization yielded the highest decision accuracy but the worst in speed. These findings point to adaptive and/or adaptable user interfaces/interactions (Jameson, 2007; Lavie & Meyer, 2010) that would enable dynamic LODs according to the need of the users and systems/situations.

Limitations And Future Work

The manipulation of LOD in this study cannot be perfectly controlled in that "content" (i.e., LODs) and forms (i.e., visualization methods) cannot be fully separated. That is, the visualizations or representational forms could not be identical across all LODs. For example, a Heat map may be more visually appealing besides containing fewer details than the Trajectory visualization. The current study assumes all the search teams have the same search capability with the same speed and accuracy. Future research should recruit SAR professionals to assess generalizability of this research.

Conclusion

This study presents the first study explicitly investigating how different LODs about an agent-based LPM could influence speed, accuracy, and workload. The LOD about autonomy impacts performance in a complex manner. The increased decision accuracy seemed to incur a cost in decision speed, indicating that LODs could induce the speed-accuracy tradeoff. Lower LODs about autonomy (i.e., more information) could reduce the subjective workload of thinking about the decisions by the autonomy, irrespective of whether the amount of information is sufficient to support the best performance. The results suggest that researchers and practitioners must pay careful attention to presenting details about autonomy to achieve desirable outcomes.

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