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Visualizing Uncertain Real Time Threat Information in Augmented Reality Aided Target Recognition: Lessons Learned From Virtual Reality Simulation

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ABSTRACT

Recent advancements in artificial intelligence (AI), edge computing, and head-worn augmented reality (AR) technology are bringing the prospect of sophisticated aided target recognition (AiTR) systems from sci-fi to reality. Future AI algorithms could augment AiTR with real-time threat assessments (RTAs) that augment Soldier decision making by providing a binary threat assessment alongside an estimate of epistemic algorithmic uncertainty through the fusion and interpretation of multiple data sources. Yet, visual representations of probability are often misinterpreted, which could have consequences when relying on uncertain RTAs. To investigate, we designed simulated uncertain RTAs in virtual reality (VR) using emerging probabilistic visualization techniques, such as hypothetical outcome plots (HOPs; Hullman et al., 2015) and discrete-outcome framing (Franconeri et al., 2021), and quantified their impact on lethal force decision making. Specifically, we extended a VR decision making task from our previous work (Gardony et al., 2022; Frontiers in VR), in which participants categorized a Soldier target advancing towards them as friendly or enemy based upon their worn camouflage pattern, overlaying continuous- and discrete-outcome framed uncertain RTAs and introducing gamification elements to encourage rapid decision making. We found that when targets were easy to distinguish, participants were more conservative when categorizing targets as enemy vs. friendly, reflecting a learned decision-making heuristic. Importantly, under conditions of relatively low perceptibility (i.e., for far-away targets), our findings suggest trust in and reliance on RTAs increased, as evidenced by attenuated conservativity that deviated from the default heuristic. These findings contribute to the emerging literature on trust in AI and have implications for the design and deployment of effective military human-AI interfaces.

Keywords: Aided target recognition, Uncertainty, Visualization, Decision making, Augmented reality, Virtual reality

INTRODUCTION

The United States Army is developing Soldier systems that integrate artificial intelligence and machine learning (AI/ML) to aid in the automatic detection, classification, recognition, and identification of potential threats. Such

Aided Target Recognition (AiTR) systems can speed warfighter decision making across a range of mission sets by providing real-time threat assessments (RTAs) in heads-up augmented reality displays while reducing engagement timelines and cognitive workload (Schachter, 2020). Yet, current target classification algorithms perform poorly in open-set conditions characterized by complex, dynamic environments that can be difficult or impossible to fully capture and represent by a training dataset (Dhamija et al., 2020). Imperfect AiTR can impair human performance by increasing false alarms and attentional tunnelling and decreasing situational awareness (Geuss et al., 2019; Matzen et al., 2020). A promising approach to mitigate these issues is to analyse the AiTR algorithm's epistemic uncertainty, or its uncertainty due to lack of knowledge, and leverage it to either automatically reject classification labels or visualize the degree of algorithmic uncertainty to the user (Miller et al., 2021), which has been shown to reduce attentional tunnelling (Cunningham et al., 2017). Thus, future Soldier AiTR systems could incorporate real- (or near-real) time estimates of algorithmic uncertainty in their RTA visualizations to optimize human-AI integration. In the present study, we developed a novel AiTR uncertain RTA visualization in a simulated augmented reality (AR) display based on data visualization best-practices and evaluated its impact on lethal force decision making in virtual reality (VR).

A central challenge to depicting uncertainty within AiTR visualizations is that the concept of uncertainty is itself difficult to understand (Franconeri et al., 2021; Matzen et al., 2023). Much research has demonstrated that mapping uncertainty to different visual encoding channels can lead to varying interpretations (Franconeri et al., 2021; Padilla et al., 2021). For example, MacEachern and colleagues (2012) found that fuzziness, location, colour value, arrangement, size, and transparency were rated in descending order of intuitiveness. However, depicting uncertainty within an AiTR bounding box using these encodings is not straightforward and could affect the AiTR's visibility and perceptibility in ways that reduce its effectiveness.

Alternatively, an AiTR bounding box could be augmented with an adjacent uncertainty visualization, but this could increase visual clutter and/or difficulty of interpretation. For example, common uncertainty visualizations like density, box, and violin plots require prior experience with the visualization and/or statistical training to accurately interpret and simple error bars are frequently misunderstood even by experts (Hofman et al., 2020; Potter et al., 2010). Hypothetical outcome plots (HOPs; Hullman et al., 2015) are a promising alternative visualization technique accessible to general users that present uncertainty as a set of animated frames that each depict a sample from a probability distribution. HOPs improve estimation of distributional information better than violin plots and error bars and can be applied flexibly across real-world applications (Kale et al., 2019).

Another best practice approach to communicate probabilistic uncertainty is through frequencies (e.g., 1 out of 10). Discrete-outcome (or frequency) framing allows the viewer to interpret probabilities by counting discrete visual elements and has been shown to more effectively communicate uncertainty than percentages, especially for low numeracy individuals (Franconeri et al., 2021; Peters et al., 2011). For example, in hurricane visualization, ensemble plots improve risk assessment (Liu et al., 2019) and icon arrays effectively communicate probability in health-care contexts (Garcia-Retamero and Cokely, 2017). Taken together, this research suggests uncertain RTAs implementing HOPs with discrete-outcome framing could be a promising approach to depict real-time epistemic algorithmic uncertainty in an AiTR system that improves decision making and human-AI integration.

In the present study, we extended a VR lethal force decision making (LFDM) scenario from our previous work (Gardony et al., 2022; Frontiers in VR), in which participants categorized a single animated Soldier avatar advancing towards them as friendly or enemy based upon their worn camouflage pattern. We overlayed uncertain RTAs modelled after HOPs, above a simulated AiTR bounding box using continuous- and discrete-outcome framing and introduced gamification elements to encourage realistic and rapid decision making. We predicted introducing uncertain RTAs would improve lethal force decision accuracy and that discrete-outcome RTAs would perform best overall.

METHODS

Participants

Thirty-six active-duty Soldiers ($M_{\text{age}} = 23.28$, $SD_{\text{age}} = 5.28$, 7 Female) voluntarily participated. Human use approvals were reviewed and approved by the United States Army Combat Capabilities Development Command Soldier Center Human Research Protection Program Office and the Tufts University Institutional Review Board. Written informed consent for participation was not required for this study in accordance with the national legislation and the institutional requirements. All participants possessed 20/30 binocular distance visual acuity or better as determined by the Snellen eye chart and normal colour vision as determined by the Colour Vision Testing Made Easy test (Cotter et al., 1999).

Materials

For full details of our virtual reality (VR) LFDM scenario, including technologies used and metrics collected, we refer the interested reader to our previous publication (Gardony et al., 2022). Below we provide a brief overview of the scenario and describe modifications we implemented for the present study.

A LFDM trial consisted of a single Soldier avatar (i.e., target) briskly walking toward the participant in an urban corridor in VR. The target emerged from the corridor's left or right side from either a far starting (spawn) location (75m) or a near location (50m), which manipulated its perceptibility. Participants discriminated between friendly/enemy targets based on their worn camouflage pattern which was parametrically mixed between a friendly and enemy pattern, affecting the informational content of the target stimulus. Participants also monitored the windows of nearby buildings for the appearance of a single non-combatant civilian, a secondary task designed to increase cognitive load. During each trial, a simulated AR bounding box surrounded the

Soldier target. Depending on the (within-participants) experimental block, participants either saw this baseline "Box" AiTR alone or with an uncertain RTA visualization included above it. Across blocks, bounding boxes also erroneously overlayed some civilians but these spurious overlays did not include RTA visualizations. Figure 1 depicts an example trial from the LFDM scenario (A) and example Soldier targets with mixed camouflage patterns (B).

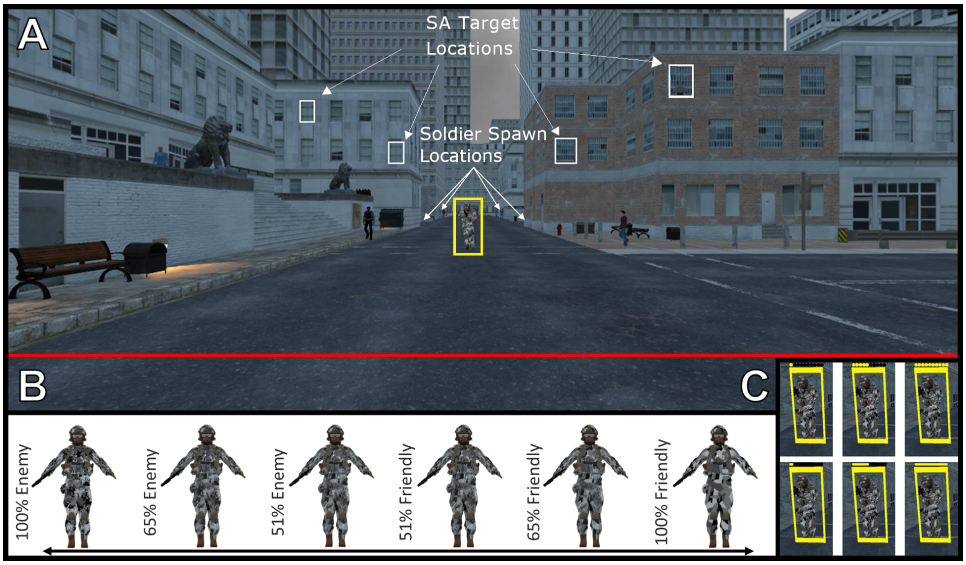

Figure 1: Example LFDM scenario trial from the box (baseline) condition. Arrows depict the four possible soldier target spawn locations and the four possible secondary target spawn locations. (B) Example soldier targets in the six possible blended camouflage patterns (left to right: 100% enemy, 65% enemy, 51% enemy, 51% friendly, 65% friendly, 100% friendly. (C) Example uncertain RTA visualizations (top row: discrete framing, bottom row: continuous framing).

In the present study, we modified the LFDM scenario to address three limitations. First, we increased secondary task difficulty by removing movement jitter of the peripheral non-combatant civilian. Second, we modified the scenario and introduced gamification to encourage rapid and realistic decision making by (1) reducing the far spawn location distance from 100m to 75m, (2) including a low-probability (0.5%) of any trial ending prematurely (i.e. enemy Soldier shoots, friendly Soldier disappears), (3) displaying onscreen accrued points that reflected primary and secondary task performance.

AiTR Conditions

In addition to the baseline "Box" condition, we evaluated two simulated uncertain RTA visualizations. These visualizations dynamically displayed an uncertain real-time threat estimate of the Soldier target, ranging from 0 ("100% friendly") to 100 ("100% Enemy"). The visualization was updated and displayed continuously (10 Hz) based on an underlying stochastic algorithm that increased the accuracy and decreased the uncertainty of the current RTA as the target advanced. In the continuous-outcome framing condition, a horizontal progress bar was filled in proportion to the current RTA. For example, if the current RTA was 75% then 3/4 of the bar would be filled. The discrete-outcome framing condition displayed a row of 10 dots. The current RTA was rounded to the nearest 10% and the corresponding number of dots was filled in proportion. For example, RTA = 75% would translate to 8/10 dots full while RTA = 33% would translate to 3/10 dots full. Figure 1, panel C presents example uncertain RTA visualizations.

Procedure

The procedure was identical to our previous study. Participants completed three blocks in a single study session, box (baseline), continuous-outcome framing, and discrete-outcome framing, in counterbalanced order. The study took about 1.5 hours to complete.

RESULTS

Data Filtering and Analysis

Prior to data analysis, we removed poor quality datasets in a principled manner. We first removed four participants due to experienced discomfort, very poor task performance, or incomplete data collection. Next, using the eye tracking data, we removed data blocks where participants were noticeably drowsy. Extant research shows that percentage of time with eyes closed (PERCLOS) is associated with drowsiness (Ftouni et al., 2013) so we approximated PERCLOS using the VR headset's gaze status metric and removed blocks where participants' gaze was invalid for > 10% (6s) of any 1-minute time window. This procedure removed 16 blocks, including three additional participants. 29 ($M_{\text{age}} = 23.65$, $SD_{\text{age}} = 5.31$, 6 Female) participants were ultimately included in the analysis. Lastly, again leveraging our eye tracking data, we removed individual trials where participants did not look at the advancing Soldier target within the first 5 seconds of the trial (< 0.1% of trials).

We used R to conduct all statistical analyses. Specifically, we fit a Bayesian generalized linear mixed models (GLMMs) using the *brms* R package (Bürkner, 2017) and used the *emmeans* package (Lenth, 2020) for follow-up pairwise comparisons. For statistical inference, we report the Region of Practical Equivalence (ROPE), Probability of Direction (PD), and 95% Highest Density Intervals (HDI).

Categorization Error Analysis

We examined categorization error of the advancing Soldier target in the LFDM scenario with a Bernoulli family GLMM using the default priors in *brms* and set the ROPE to $\pm 1\%$. The model included four fixed effects: Camo Clarity (CC: 51CC, 65CC, 100CC), Spawn Distance (SD: Far, Near), Participant Response (PR: Enemy, Friendly), and Real-Time Threat Assessment (RTA: Box, Continuous, Discrete) with by-participant random intercepts.

Categorization error differed between the CC and SD conditions (see Tables 1 and 2). The analysis provided strong evidence that error rates were highest for 51CC targets relative to 65 and 100CC and were higher for far spawning targets relative to near. There was little evidence that RTA condition or participants' responses themselves influenced categorization error.

We next examined interactions, which revealed a conservative enemy categorization bias (CECB) where participants committed fewer errors when categorizing enemy vs friendly targets with high informational content (i.e., 100CC, see Table 3). The observed response trends in each CC condition corroborated this finding. Overall, participants responded enemy 34% of the time (66% friendly) for 100CC targets, 55% enemy (45% friendly) for 65CC targets, and 41% enemy (59% friendly) for 51CC targets. Further analysis provided strong evidence that a CECB was evident for near but not far spawning 100C targets. Specifically, we found that for near-spawn 100CC targets, the CECB was consistent across all RTA conditions. However, for far-spawns, both RTAs eliminated the CECB effect which persisted in the Box condition (see Figure 2).

Table 1. Categorization error estimated marginal means (EMMs) by camo clarity (CC) and pairwise contrasts with 95% HDIs, % in ROPE (%R), and probability of direction (PD).

CC	EMM	95% HDI	Contrast	Δ	95% HDI	%R	PD
51	0.48	[0.44, 0.52]	51–65*	0.18	[0.13, 0.23]	0	100
65	0.30	[0.26, 0.34]	51–100*	0.21	[0.16, 0.26]	0	100
100	0.27	[0.24, 0.30]	65–100	0.03	[−0.02, 0.08]	20	86

Table 2. Categorization error estimated marginal means (EMMs) by spawn distance (SD) and pairwise contrasts with 95% HDIs, % in ROPE (%R), and probability of direction (PD).

SD	EMM	95% HDI	Contrast	Δ	95% HDI	%R	PD
Far	0.40	[0.37, 0.43]					
Near	0.30	[0.28, 0.33]	Far–Near*	0.10	[0.05, 0.14]	0	100

Table 3. 100% camo clarity categorization error estimated marginal means (EMMs) by participant response ([E]nemy, [F]riendly), spawn distance ([F]ar, [N]ear), and RTA ([B]ox, [C]ontinuous, [D]iscrete) and interaction pairwise contrasts with 95% HDIs, % in ROPE (%R) and probability of direction (PD).

PR	SD × RTA	EMM	95% HDI	Contrast	SD × RTA	Δ	95% HDI	%R	PD
E	N, B	0.10	[0.01, 0.22]						
F	N, B	0.34	[0.24, 0.44]	E-F*	N, B	−0.23	[−0.38, −0.06]	0	99
E	N, C	0.10	[0.02, 22]						
F	N, C	0.27	[0.17, 0.29]	E-F*	N, C	−0.14	[−0.32, −0.01]	0	98
E	N, D	0.05	[0, 0.14]						
F	N, D	0.28	[0.18, 0.39]	E-F*	N, D	−0.23	[−0.36, −0.10]	0	100
E	F, B	0.18	[0.06, 0.34]						
F	F, B	0.38	[0.28, 0.49]	E-F*	F, B	−0.19	[−0.36, 0.01]	1	97
E	F, C	0.39	[0.01, 0.22]						
F	F, C	0.39	[0.23, 0.44]	E-F	F, C	0.00	[−0.18, 0.20]	9	51
E	F, D	0.33	[0.20, 0.47]						
F	F, D	0.37	[0.25, 0.49]	E-F	F, D	0.04	[−0.21, 0.15]	7	66

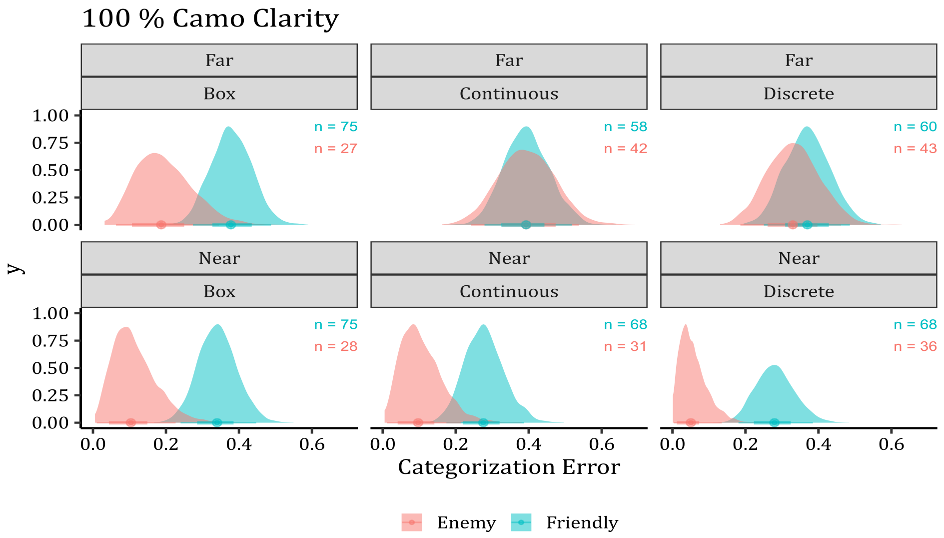

Figure 2: Kernel densities of the estimated marginal means of the expected values of the categorization error posterior predictive distribution by spawn distance, RTA, and participant response for 100% camo clarity targets. Median point estimates (dots) and 66% and 95% highest density intervals (HDIs) are also depicted. Inset frequencies denote the number of observed responses for each response type.

DISCUSSION

In the present study, we investigated how uncertain real-time threat assessments (RTAs) influence lethal force-decision making (LFDM) using virtual reality. Participants categorized advancing Soldier targets as either friendly or enemy based on their worn camouflage pattern that varied in perceptual discriminability. Building on our previous study (Gardony et al., 2022), we incorporated RTA displays that presented real-time uncertain threat information using continuous- and discrete-outcome framing and introduced gamification to encourage rapid decision making that better reflected real-world LFDM. We found that under conditions of relatively high informational content but low target perceptibility, both discrete- and continuous-framed uncertain RTAs reduced conservative enemy categorization bias suggesting trust in AI-enabled RTAs increases when targets are difficult to perceive.

To manipulate target perceptibility, we used two Soldier target spawn distances (far, near). As the Soldier advanced toward the participant, their camo pattern became more perceptible (and thus less uncertain). To manipulate the target's informational content, we used three levels of camo clarity (CC; 51%, 65%, 100%) with greater CC having more informational content (and less uncertainty). As expected, participants more accurately categorized 100CC and 65CC targets relative to 51CC. Similarly, participants more accurately categorized near vs far targets. Taken together, these findings demonstrate that both stimulus perceptibility and informational content impacted decision accuracy.

Upon further inspection, we discovered an interaction where participants tended to categorize high informational content (i.e., 100CC) targets as friendly more often than enemy but this conservative enemy categorization bias (CECB) was not evident for lower informational content targets (i.e., 65CC and 51CC). This suggests that with greater informational content, participants were more conservative when categorizing targets as enemy (i.e., greater CECB), reflecting a learned decision-making heuristic from their military training (e.g., avoid friendly fire). Further investigation revealed that this CECB effect was observed for both the near- and far-spawns for the Box condition, suggesting that Soldiers exhibited the CECB when making decisions based solely on their visual perception. However, when assisted by an uncertain RTA, CECB was eliminated when target perceptibility was relatively low (i.e., far-spawn targets). This suggests that when a potential target has high informational content and high perceptibility, participants place greater trust in their perception than the uncertain RTA visualization. However, when they interrogate a high informational content target with low perceptibility, their trust in the RTA increases, leading to deviation from default decision-making heuristics (i.e., CECB). These findings contribute to the emerging literature on trust in AI and have implications for the design and deployment of effective military human-AI interfaces.

Limitations of our findings should be noted. In our effort to encourage realistic and rapid decision making, we introduced several gamification elements which successfully reduced average response time (RT) in the LFDM task from 15.7s ($SD = 7.7$, range = 2.8–29.3) in our previous study to 3.3s ($SD = 2.7$, range = 0.2 – 18.56) in the present. Introducing gamification also substantially reduced RT variability, indicating that participants' RTs were much more consistent. However, due to a regrettable coding error, far-spawn target RTs had a $\sim$1s variable delay while no such delay was observed for the near-spawn targets. This made RT analyses difficult to interpret and were therefore omitted from analysis. Lastly, we acknowledge that despite the introduction of gamification, laboratory research like the present study cannot fully replicate the real-life lethal force decision making of real-world military operations so the generalizability of our findings should be interpreted with care.

CONCLUSION

The present study contributes to the growing literature on how aided target recognition (AiTR) visual designs impact perception, cognition, and decision making. We explored how two simulated uncertain real-time threat assessments (RTAs) designed to aid Soldiers in detecting threats when using AiTR systems impacted lethal force decision making. Our findings suggest that under conditions of relatively high target perceptibility, users preferentially trust their own visual perception over uncertain RTAs. However, under conditions of relatively low perceptibility, trust in RTA increases, leading to decision making that deviates from default conservative heuristics. Further investigation and refinement of AiTR visual designs will become increasingly important as future Soldier AiTR systems are developed, refined, and implemented for military applications.

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DISCLAIMERS

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