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Analyzing the Impact of Improved Situational Awareness on Command and Control System Performance for Decision-Making

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Abstract: Situational awareness (SA) provided by military decision support systems is limited by the lack of an effective method for displaying information uncertainty, which can hinder subsequent Command and Control (C2) decision-making. This work proffers a methodology to assess how SA and subsequent C2 decision-making are improved via the characterization of information uncertainty in an artificial intelligence-enabled aided target recognition use case leveraging a common operating picture displayed on a Tactical Awareness Kit (TAK). A TAK-integrated One Semi-Automated Forces solution is used to simulate and assess user SA and C2 decision-making effectiveness in experiments with varied conditions of information uncertainty.

Keywords: *Situational Awareness, Command and Control, Decision-Making, Information Uncertainty, Simulation, COP*

1. Introduction

Military leaders face complex challenges on the battlefield, requiring them to make difficult, timely decisions. To enable effective command and control (C2) for this decision-making, information fused from various data sources are integrated into a military decision support system (DSS) and presented on a Common Operating Picture (COP). COPs present information to provide commanders' situational awareness (SA), a key element of understanding a battlefield situation and making effective decisions (Matthews et al., 2001). A key data source that feeds into modern COPs is Aided Target Recognition (AiTR) output, where artificial intelligence (AI) -based object detection models are used to analyze data from sensors (e.g., images from aerial drones) to identify and recognize objects for potential targeting. AiTR outputs can be displayed on map visualizations in the COP with markers to indicate the locations of objects of interest (e.g., friendly and enemy soldiers, vehicles, and command posts). The COP information display includes the ability to identify, nominate, and weaponeer dynamic targets, for example. The enhancement of SA that a COP provides can lead to improved C2 system performance and mission effectiveness. However, current COPs do not yet convey the object detection model output uncertainty associated with AI model predictions.

In general, COP effectiveness is limited by several factors including being displayed on small screens for portability, interface designs that may not be user-friendly, and functionality that provides inadequate SA. We focus on SA deficits arising from the lack of a standard effective method for displaying information uncertainty. Several types of uncertainty are relevant for a COP, including uncertainty about an object's precise location and its classification. We focus on the latter, as AI-enabled AiTRs do not conclusively classify an object but provide an array of possibilities with associated probabilities. Operating without awareness of the uncertainty associated with an object's identity compromises SA. We hypothesized that incorporating uncertainty information in a COP will improve SA and decision-making for commanders and battlefield decision-makers.

For example, a platoon leader (PL) might be deciding whether to initiate an attack against an enemy element that the AI-enabled AiTR classified as most likely squad-sized. However, the PL might make a different decision if they were made aware that, although the element is most likely a squad (52% probability), the AiTR also assigned a 48% probability to the possibility that it could be an enemy platoon, a much larger unit. A PL might opt not to engage with an enemy unit if there is a high level of uncertainty about its strength and composition. Thus, it would benefit SA and decision-making if the COP effectively conveyed such information uncertainty. Numerous methods exist to analyze SA, but none, to our knowledge, explore the interaction between the display of information uncertainty and SA (Breton, Tremblay, & Banbury, 2007).

Simulation is a possible approach to assess the benefits of representing information uncertainty on a COP. With minimal cost and almost no risk, tools such as One Semi-Automated Forces (OneSAF) - a commonly used software simulation tool within the operational Army - can estimate alternative battlefield outcomes that could arise when elements of the situation are varied (e.g., resources, force size, and courses of action chosen). To the best of our knowledge, no solution exists to visualize the outputs of a simulation tool (e.g., OneSAF) on a digital COP (e.g., TAKX) to allow for convenient, rigorous assessment of design aspects/elements crucial to C2 system performance. If a military leader can simulate a battlefield scenario on the COPs they use to make decisions, they would be able to understand better the consequences of different actions with effectively no risk. Additionally, using the same COPs to visualize uncertainty can potentially improve SA and battlefield effectiveness.

Our contributions herein are two-fold. We developed (1) a method to integrate the results of an Army simulation tool into a modern and widely fielded C2 system's COP, and (2) a novel methodology to assess how the visualization of information uncertainty may improve SA, particularly in an AI-enabled AiTR use case. OneSAF is leveraged to simulate realistic ground forces as an input to our COP. We then integrate representations of uncertainty and measure the impacts on user SA and decision-making. We believe these contributions will assure the replication of future evaluations in varying tactical scenarios and allow COPs to effectively display information uncertainty, creating better-informed, more effective battlefield decision-making.

2. Literature Review

A C2 system, a C2 process enabled by a military DSS, is capable of analyzing data and providing support for solution generation (Liu, Duffy, Whitfield, & Boyle, 2009). These systems, created from collecting, fusing, and displaying information from multiple sources and sensors, have been shown to enhance SA (Munir, Aved, & Blasch, 2022). Visualizations of these systems can also be called COPs. Because increased SA increases effective decision-making, analyzing what leads to increased SA is vital to improving C2 (Munir et al., 2022). A tested method for measuring SA is the Situational Awareness Global Assessment Technique (SAGAT), which freezes a simulation and asks questions to evaluate individual SA (Breton et al., 2007). C2 systems may include AI-enabled AiTR, which is the automated process of utilizing imagery sensors and computer vision to aid military leaders in making decisions with lethal actions. This technology includes uncertainty from the training data used to build the AI model, the environmental effects on the sensors, and the autonomy left vested in the system (Huffman, 2011). A primary difficulty in improving SA within C2 systems is the understanding and display of uncertain information.

AI models, such as those powering AiTR technology, inherently have uncertainty surrounding their predictions. Measuring and quantifying these uncertainties is complicated, given how AI models are trained on sample data (Psaros, Meng, Zou, Guo, & Karniadakis, 2023). Although there have been no systematic investigations toward effectively quantifying total uncertainty, there has been work on uncertainty quantification (UQ) in neural networks (Psaros et al., 2023). Two widely used types of UQ are Bayesian approximation and ensemble learning (Abdar et al., 2021). These methods of UQ are too computationally expensive, so we leverage a newly created certainty and competence framework (Berenbeim, Cobb, Roy, Jha, & Bastian, 2025).

There is some prior work on representing information uncertainty (Harrower, 2003), but to our knowledge, there is no standard method for displaying information uncertainty on a C2 system's COP. Although graphically displaying uncertainty is significantly more effective than exclusively displaying uncertainty numerically or not displaying it at all, little to no effort has been made to analyze the graphical display of information uncertainty (Bisantz et al., 2011). The optimal display of this information is crucial for COP user-friendliness, the aspect often considered the most critical piece of a COP (Harrington, 2002). Assessment of the effectiveness of a COP is also difficult, considering the complications of testing complex decisions in a battlefield environment. To circumvent the need for a live exercise to provide inputs for the TAKX (C2 system), we utilized a OneSAF-generated simulation, informed by an operational vignette, to drive the TAKX to enable user assessment. This method allowed us to experiment with designs to represent information uncertainty in a relatively inexpensive and replicable manner.

3. Methodology

Our methodology included stakeholder analysis, operational vignette design, building a OneSAF simulation, populating TAKX with simulation outputs (versus requiring a live scenario), designing iconography to represent AiTR uncertainty, creating a protocol to assess how the designs impact user decision-making and SA, and an in-person user assessment.

3.1. Stakeholder Analysis

We identified 17 organizations, including multiple military organizations and academic institutions, to provide input to inform our work. The organizations were categorized into stakeholder types (owner, decision maker, consumer, client, or interconnected), based on each organization's role(s) in advancing C2/AiTR, SA measurement, or modeling and simulation. We grouped the organizations into three focus groups based on which content area they advanced. The first group was "Measuring C2/COP Design." Individuals in this group received a survey with questions about SA, its measurement, and the interaction between SA and COPs. We then hosted an online meeting for focus group members to elaborate on their responses and provide more perspective. This process was repeated with the other two focus groups. The "C2/AiTR" group responded to questions related to the relationship between AiTR and C2 systems, and the enhancement of C2 systems. The "Modeling and Simulation" group responded to questions related to simulation development and COP integration possibilities. After collecting responses and insights from each focus group, we consolidated the information into a Findings, Conclusions, and Recommendations (FCR) matrix. This FCR matrix directly aided the design and development of our solution methodology, depicted in Figure 1.

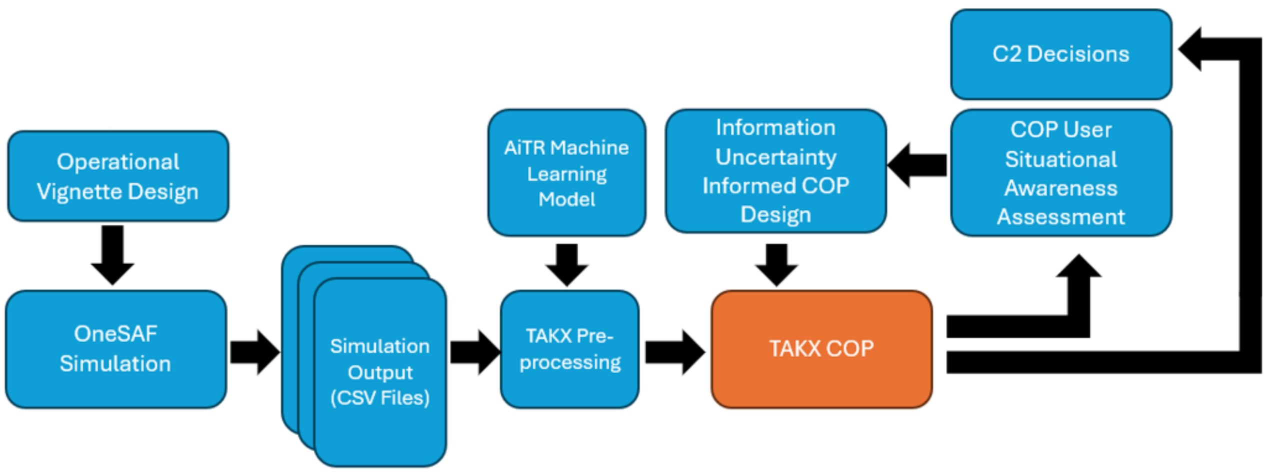

Figure 1: Solution Methodology

3.2. Solution Methodology: Design and Development

3.2.1. Operational Vignette Design

A vignette was developed to provide an operational context to assess the potential decision-making and SA benefits of providing information about AiTR uncertainty on a TAKX COP. The scenario shown in Figure 2a places the user in the role of the PL leading a light infantry platoon on a mission to attack a suspected near-peer enemy command post (top right). The PL is authorized to neutralize enemy units they may encounter, but a primary goal is to minimize friendly and non-combatant casualties. At each of three decision points (yellow stars), the PL must make a binary decision (e.g., choose avenue of approach 1: AoA1 or AoA2) based on information displayed about the enemy's location and disposition. The COP iconography shown in 2a is a control condition that displays no uncertainty information; icons displayed represent each object's most probable identity. Each of the three decision points includes varying amounts of AiTR prediction uncertainty. Near AoA1 is a green square as the hypothetical AiTR classified the group as most likely non-combatants (55%), but possibility two was an enemy squad (45%). Test users whose TAKXs show such information about uncertainty may forgo this shorter route for AoA2. Similarly, there are most likely enemy squads on AoA3 (55%) and AoA4 (90%), but on AoA3 it could be an enemy platoon (45%). The last decision is whether to do more reconnaissance (risking detection) of the suspected command post (70%) or engage with artillery, which might be affected by the knowledge that it might be non-combatants (30%).

3.2.2. OneSAF Simulation

We operationalized our vignette into a dynamic OneSAF simulation in which the friendly platoon's route was the path to minimize casualties (as per CONOP). Figure 2b depicts the OneSAF simulation, matching Figure 2a. OneSAF produced CSV output files with information on entity types, locations, and movements. Uncertainty representations were added in TAKX.

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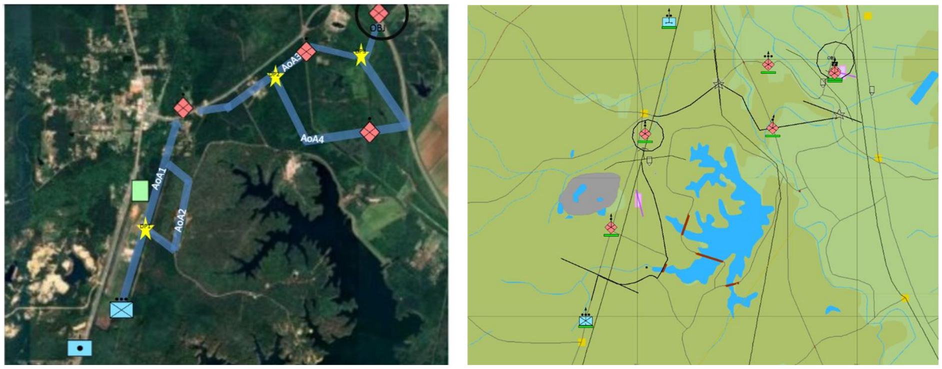

(a) Operational Vignette (b) OneSAF Simulation

Figure 2: Operational Vignette to OneSAF Simulation Mapping

3.2.3. TAKX Pre-processing

To display the OneSAF simulation on TAKX, we re-formatted the OneSAF CSV files to meet TAKX plugin requirements. We used the Windows version of TAKX for ease of data pre-processing/integration. The CSV files provided entity names, latitude, longitude, elevation, etc. We developed a Python script that first ingested the data from the extracted OneSAF CSV files and then normalized the time stamps, removed special characters from the entity names, converted locations from a geographic coordinate system to geodetic coordinates, and converted the speed from meters per second to miles per hour. We then generated a CSV for each entity with details regarding their activities in the simulation.. The entity CSV files were loaded into TAKX and the movements of all entities with their decision points were displayed using playback mode (see Figure 3).

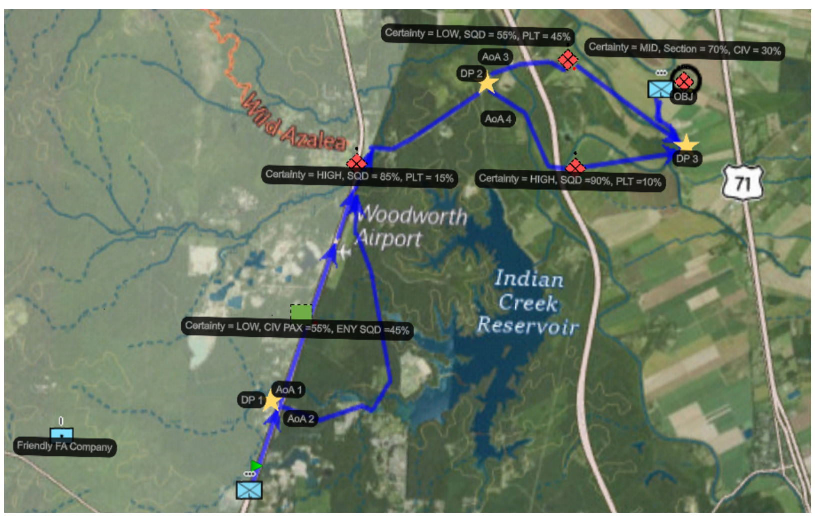

Figure 3: C2 System (TAKX) COP

3.2.4. Design and Assessment of Iconography Representing Information Uncertainty

An AI-powered AiTR system trained on N object classes outputs an N-dimensional probability vector for each detected object. The value in a given vector position is the probability that the current object matches that class. We quantify uncertainty via a certainty score based on the probability difference between the two most probable classes (Berenbeim et al., 2025). We binned certainty score values into high (0.7-1.0), medium (0.3-0.7) and low (0.0-0.3). Score aside, we presume that useful uncertainty information should include the top two most probable classes and their probabilities.

Existing military icons on COPs do not include identity uncertainty information. The icon used represents the most probable identity. This was our **control condition**. We then designed two ways to represent uncertainty by adapting doctrinal symbols to capitalize on users' training and existing knowledge. Our **label condition** adds a label below the icon for the most probable identity to specify the probabilities for the two most likely identities - e.g., [ENY SQD=70%, ENY PLT=25%]. Since the graphically detailed label condition may cause excess clutter on the map or information overload for users, our **dot+hover condition** features just a colored dot (Red, Amber, or Green) at the bottom right of each icon indicating the certainty score level (Figure 4). Details about the probabilities from the label condition appear 'on demand' if they hover over the icon (Figure 5).

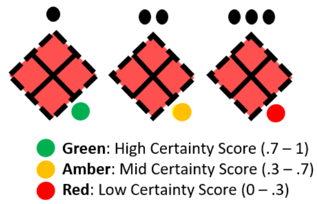

Figure 4: Updated Iconography

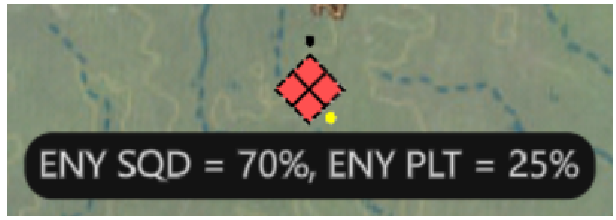

Figure 5: Iconography Hover Example

In a between-groups user assessment, each user (a PL) interacted with the OneSAF-simulated operational scenario in one of the three TAKX interface conditions. As per SAGAT methodology, at decision point pauses, users answered SA questions and reported decisions and rationales. An example SA question was: "Which route is most likely to offer fewer sustained casualties for your platoon ?" User responses and feedback can inform COP design to optimize C2 decision-making.

4. Results and Discussion

We compared our three conditions via an assessment with 12 users. Unlike control users, label and dot+hover users could access the top two possible identities for an object and their probabilities (Figure 5). Table 1 reveals that at decision-point pauses, the label interface yielded the highest SA about the nearest enemy unit, and it ensured that a higher percentage of relevant probability information was read than in the dot+hover interface (requiring users to hover). Users' decision rationales suggested that novel uncertainty information had to compete with other information that was more familiar and emphasized in prior training (e.g., route length, visibility, and terrain). Users likely require more training and practice with the novel uncertainty representations to fully capitalize on this information. With three binary decisions, there are eight possible 'paths' in the operational scenario problem space. To establish an optimal performance baseline, the implemented OneSAF-simulated scenario took the path to minimize friendly casualties. Descriptive statistics for 30 simulation runs are shown in Table 2. Such metrics for all eight decision combinations could inform the assessment of our three conditions by assigning each user the mean casualty metrics for their chosen path and aggregating by condition.

Table 1: User Assessment Results: SA, Influence of Uncertainty on Decisions, Representation Usability

Outcome Measure	Control	Label	Dot+Hover
SA: Direction of Nearest ENY (% Accuracy)	62.5%	87.5%	66.7%
SA: Size of Nearest ENY (% Accuracy)	55.5%	70.8%	58.3%
Decision rationales referring to information uncertainty	33.3%	70.8%	95.8%
Self-reported impact of uncertainty information on decisions	N/A	89.5%	93.3%
Percent of decision-relevant probability information read	N/A	100%	75%
User-friendliness of uncertainty representations	N/A	84.3%	87.5%

Table 2: Operational Measures for Casualty Rates in Baseline OneSAF Simulation

Operational Measure	Friendly	Enemy
Mean Casualty Rate	14.3%	67.1%
Standard Deviation of Casualty Rate	9.3%	32.9%
Maximum Casualty Rate	33.1%	100%
Minimum Casualty Rate	1.4%	10.4%

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5. Conclusion

Our work presents a novel, repeatable methodology to explore the impact of different ways to enrich the information on a C2 system (TAKX) COP. Our label and dot+hover designs provided uncertainty information about AiTR target identities. To enable low-cost, low-risk user assessment, we designed an operational vignette, simulated it in OneSAF, and used the OneSAF output to populate the TAKX display with a dynamic scenario (with pauses at decision points to assess user SA). The label interface provided the highest SA and ensured that users read all relevant probability information (no hover requirement). Limits of this research include having a small sample of users, and only two alternative designs for representing information uncertainty. To improve the resilience, effectiveness, and ethical grounding of military decision-making there is a need for focused academic research and engineering innovation tailored to the complexity of military operations. By incorporating effective depictions of information uncertainty, military leaders can act with improved SA and make better-informed and sounder decisions.

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