The Impact of Message Quality on Entity Location and Identification Performance in Distributed Situational Awareness

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DEDICATION

This is dedicated to my loving wife, Rebecca, and my friends and mentors who helped me on finishing this audacious task.

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LIST OF ACRONYMS

AMSAA -Army Materiel Systems Analysis Activity
AOI -Areas of Interest
AiTR – Aided Target Recognition
C2 -Command and Control
C4ISR - Command, Control, Communications, Computers, Intelligence, Surveillance, and Reconnaissance
CDF -Cumulative Density Function
CTF -Contrast Threshold Function
CTI -Cooperative Target Identification
DSA – Distributed Situational Awareness
EMS – Electromagnetic Spectrum
EO -Electro Optical
FAR - False Alarm Rate
FLIR -Forward Looking Infrared
FMV -Full Motion Video
FOCUS -Fusion Oriented C4ISR Utility Simulation
GLU – Geographical Location Uncertainty
HVS – Human Visual System
IEEE - Institute of Electrical and Electronics Engineers
IR -InfraRed
ISR -Intelligence, Surveillance, and Reconnaissance
LiDAR -Light Detection and Ranging
MOE -Measures of Effectiveness
MOP -Measures of Performance
MQ – Message Quality
NVESD -Night Vision Electronic Sensor Directorate
NV-IPM - Night Vision Integrated Performance Model
P_{Inf} -Probability of Detection given Infinite Time
P(d) -Probability of Detection PETS
SA – Situational Awareness
SAR -Synthetic Aperture Radar
STS – Socio Technical Systems
TL – Task Load
TTPM -Targeting Task Performance Metric
WAMI – Wide Area Motion Imagery
WM – Working Memory

UAS -Unmanned Aerial System
V&V -Verification and Validation
VV&A -Verification, Validation and Accreditation
VCA – Video Content Analysis

ABSTRACT

THE IMPACT OF MESSAGE QUALITY ON ENTITY LOCATION AND IDENTIFICATION PERFORMANCE IN DISTRIBUTED SITUATIONAL AWARENESS

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George Mason University, 2019

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There are many organizations where location and time are critical to the success of their mission. These organizations desire to improve the performance of their teams with the technology they are using to locate an entity in the minimal amount of time as necessary. The study of this optimization is titled visual analytics, which studies the performance of humans and machines on a specific task. For this work, the task is detecting and identifying a specific entity, a team task consisting of two analysts, verbally communicating together in order to collaborate on completing their task. With the message quality of this communications impacting the outcome of their performance due to its effect on their situational awareness of the situation.

To address this question, a simulated environment was created using the program FOCUS. This simulation replicated two unmanned aerial systems – operated by two human analysts (simulated), each carrying a different electro-optical sensor, over a complex, urban environment. A yellow taxicab acted as the specific entity the two analysts tried to detect and identify by utilizing targeting performance measures. This function was evaluated within the simulation against different levels of message qualities (low, medium, and high quality) that was incorporated into the same level of situational awareness and based on the training level of the team. These levels were measured 500 times for each level to determine the impact on the performance of the tasks. This was accomplished through the utilization of the distributed situational awareness theory.

The results showed a significant difference between each level of situational awareness, impacted by message quality. It also supported that each level was significantly better than the result of the lower level. This provides additional evidence that training on communications improves the performance of the team and creates a baseline of performance based on situational awareness. When aided target recognition technology was incorporated into the experiments, however, the added technology did not produce significantly different performance results compared to the high level of situational awareness and training.

For those organizations that location and time are important to mission accomplishment, these results provide an additional resource on the how technology and training might be utilized to find the best performance given certain situations. A highly trained team might improve their performance with this technology, or a team with low training could perform at a high level given the appropriate technology in limited time scenarios. More importantly, this provides an evaluation tool to compare new technologies and their impact on teams. Is an investment in new technology appropriate if investing in additional training produces the same performance results? Future performance can also be evaluated based on the team's level of training and use of technology for these specific tasks.

1. INTRODUCTION

1.1. Introduction

At the cross roads of human cognition and electronic data processing is the field and study of visual analytics. Within this area of study, the overarching goal is to develop a greater basis of understanding on the methods, technologies, and practices that exploit and combine the strengths of human and computer processing (Keim, et al. 2008). On one side of this combination is the human being, equipped with eyes and brain to analyze their surroundings. Historically, our ancestors needed to investigate their environment to find food, protect themselves from predators, and also maintain a safe area to live. As we progressed over the eons, the advent of computers and an increasingly technological society have stressed our capacity to handle all of the visual information that assaults our senses. Research by Misra and Stokols (2012) indicates that we are limited by our biology (the human brain) in how much data our human visual system and organic cognition abilities can handle in a specific amount of time. Too much data leads to information overload and after our limit is reached, we quickly loose visual images as the brain erases old data in lieu of the new. As described by Kerren et al. (2011) as more unfiltered information is collected and stored, a predicament arises which they label the "information overload problem." This refers to the vast amounts of information that is of no value to the person because it is irrelevant to the task or processed and/or presented in an unsuitable way to make it worthless. Consisting of emails and other forms of communication that hinders a person's ability to make timely and informative decisions (Einsfeld et al. 2009). This problem also increases the stress upon a person which ultimately effects their ability to perform and complete tasks (Entin and Serfaty 1999).

For this work and based on this research, the premise is that the human brain can only detect a finite number of objects and then even less if it has to identify a specific one. A couple of entities might not be a problem, but an urban environment full of different entities and consisting of a complex environment would overload the capacity of the human brain – even several people working together. Therefore, the problem isn't acquiring data but identifying methods and models that can turn this information into reliable, provable, and actionable knowledge (Kerren et al. 2011, 2013). Past research conclusions have applied a common fallacy to the problem of information overload by indicating that to fix it, people only need better technology - more powerful tools to automated data analysis and present relevant information (Keim et al. 2008) Other research indicates that this might solve an immediate problem but also creates a placebo effect that this new technology is making a difference; however, these devices usually don't help us understand the problem any better and will likely lead to more complicated problems in the future. Visual analytics provides a methodology to assist in understanding the problem of understanding and "analyzing our analysis" to determine if low cost processes and procedures can be incorporated into complex data analysis instead of costly technological solutions (Andrienko et al. 2011a). To provide a guideline for this process, this work will utilize the overarching vision of visual analytics. This goal is to turn information overload into an opportunity with the goal being to make data or information processes more transparent to analytic techniques (Thomas and Cook 2005). Visual analytics will be further examined in section 2.1.

Being highly interdisciplinary, visual analytics combines various related research areas such as visualization, data mining, data management, data fusion, statistics and human factors science (among others). As described by Thomas and Cook (2005) the goal of merging these disciplines together is the creation of tools and techniques to enable people to:

- Synthesize information and derive insight from massive, dynamic, ambiguous, and often conflicting data.
- Detect the expected information and assist in discovering unexpected data.
- Provide timely, defensible, and understandable assessments.
- Communicate assessment effectively for action.

Keim et al. (2008) visualize this merging in Figure 1 by creating a subjective division in labor between the machine (electric data processing) and the human being that makes sense of the information they are viewing through the human visual system.

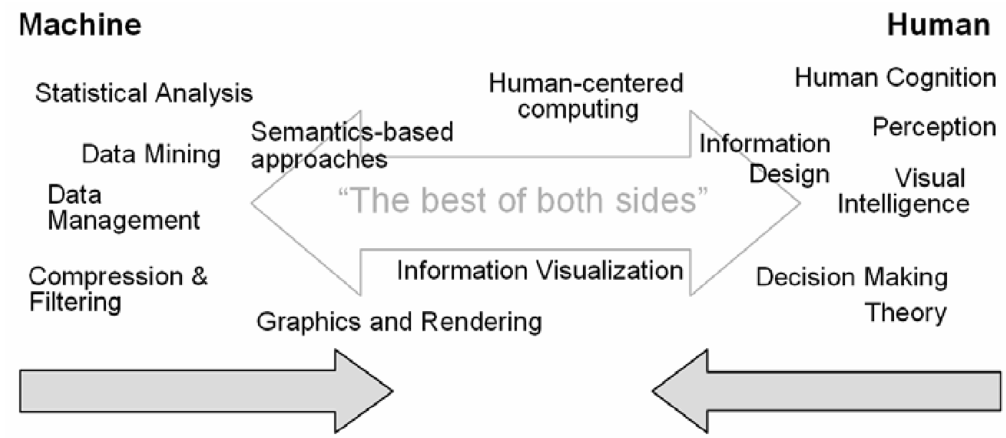


Figure 1 Visual analytics integrates scientific disciplines to improve the division of labor between human and machine. Source (Keim et al. 2008).

However, visual analytics is more than just visualization. It is an integral approach to decision-making, combining visualization, human factors, and data analysis (Keim et al. 2008; Andrienko et al. 2013). The challenge is to optimize the interaction between the two for the task at hand, estimating limits that can't be further automated and then develop a tightly integrated solution that adequately integrates the best-automated analysis of the processes with appropriate visualization and interaction techniques (Hansen and Johnson 2011)

For example, and to better describe this work's problem statement, the U.S. military leverages these two strengths, machine and humans, to find and then identify an entity for various reasons. Over a decade of continuous military operations within Afghanistan and Iraq (and other countries) have rapidly evolved and enhanced the field of visual analytics due to the nature of these conflicts and required changes in technologies and procedures. Driving this change was the Department of Defense's (DoD) need to find a decentralized enemy that easily blends with their native populations; therefore, many different methods, technologies, and practices were quickly funded, fielded, and tested to determine their ability to correctly identify and track terrorists or enemy participants (Odom 2008; Frank 2012)

Machine or technological solutions focused on sensors and platforms that rapidly evolved and changed from space bound or high-altitude platforms to ones much closer to the ground. Additionally, electronic hardware and software packages were developed to quickly analyze data differences, provide correlations, or even automatically track distinct objects in real-time (Moore 2004; Odom 2008). The rationale behind this decision being that high-resolution images were required to detect and identify individuals or other entities and today's technology require sensors, and in particular cameras, to reduce the distance to these smaller entities (Gettleman and Schmitt 2009). Coupled with the advancing data processing technology, technical solutions became an important part of the solution to finding these individual entities.

Since most images are still viewed by human beings, and it is they who apply meaning to these pictures, these people must also be trained in finding particular images out of a complex environment. A chapter in this education for those working in the military or government is the "Yellow Taxicab Problem." It is one of many lessons that have come to epitomize an increasingly important type of object detection problem – finding a specific type of entity to be identified, discover some unknown number, if any, of those entities in imagery (static or motion), and find a specific one based on prior knowledge. Describing the search for Saddam Hussein in 2003, the “Yellow Taxicab Problem” lays out how Saddam Hussein eluded coalition forces in their attempt to capture him within Baghdad. Intelligence reports indicated that he was frequently traveling around Baghdad in a yellow taxicab; however, analysts, the humans, were unable to regularly and accurately identify such a small entity in satellite imagery (Moore 2004; Odom 2008). In training, analysts use this problem to determine other methods or processes to find such a small object in a large, complex environment. Some problems are also mitigated with technical solutions (Grossman 2014).

Another lesson example is based in Somalia with the difficulty of trying to identify “technicals” – militarized pick-up trucks usually painted white with a large weapon in the back – using space-based imagery (Odom 2008; Gettleman and Schmitt 2009). Evidence showed that the analysts could not accomplish their job without technical solutions; thus, propelling the development of new sensors, platforms, and data processing systems. Ultimately, high-resolution images were required with sufficient clarity to identify these weapon systems.

1.2. Understanding the Problem

For this work, the problem mirrors these examples. Utilizing visual-based or optical sensors attached to aerial platforms, and as shown in Figure 2, a human operator wants to find and identify a specific entity in a landscape. To better visualize the problem, this could be an aerial law enforcement platform looking for a criminal a park service platform looking for a lost hiker in a dense forest, military analysts looking for a yellow taxicab in Baghdad.

In order to accomplish this task, the operator utilizes machines, in this case aerial platforms, that house specific optical sensors to sense the landscape through the electromagnetic spectrum (EMS). Utilizing enhanced data processing systems, that raw EMS data is translated into a medium understood by the human operator through a computer and displayed on a monitor (Vollmerhausen 2004).

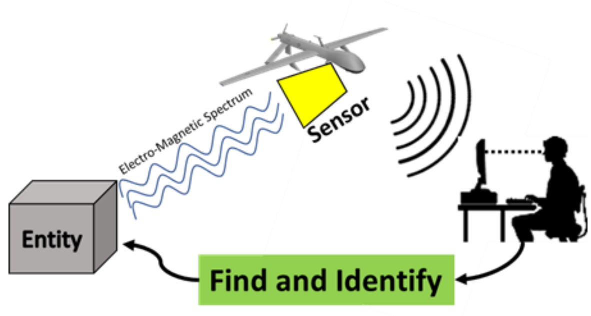


Figure 2 Diagram describing problem of this work, involving a human operator and technology required to find a specific entity.

As described in the “Yellow Taxi Problem,” the human operator would fly the platform around the landscape looking for a specific entity using optical sensors. Utilizing the visual analytics methodology, this problem would integrate human performance, decision-making, and technology limitations to identify the best process for finding and identifying a specific entity utilizing different visualization and interaction techniques. To simplify, the problem is to evaluate a sensor system (or system of systems) while incorporating the capabilities and limitations of the human beings operating these machines.

Despite merging the strengths of the machine or technical solutions and human advancements, research has shown that systems comprised of interacting human and machine agents are very complex, poorly understood, and difficult to predict (Ahmed et al. 2014). Some human performance issues have been examined such as NextGen future air traffic managements systems (Joint Planning and Development Office 2010), network centric military operations (Nelson et al. 2004), and emergency response (Manoj and Baker 2007). However, research has indicated a need to better understand the complex interactions between technological systems and human performance.

Research in this area falls under the category of “human – computer interaction” which involves the design, implementation, and evaluation of interactive technological and human systems in the context of a specific task (Dix 2004; Hernandez and Moreno 2019). Evidence is drawn from other disciplines like computer science, system design, and behavioral science with the goal of improving the interaction between humans and computers and improving the performance of completing a task (Sears and Jacko 2009). Combining and integrating the strengths of computers and humans, the focus of visual analytics, and specifically this work, is to determine an optimal interactive process designed to extract useful knowledge from data. In this work, this is presenting the data from the sensor in a format that a human operator can separate a specific entity from background clutter of an image. In order to layout the tasks for the computer and human, and their interactions, it is crucial to understand a human's cognition and how this connects to what they want to accomplish and the computer's understanding of the human's task (Keim et al. 2008).

As per the Merriam-Webster dictionary (2018a), "cognitive" is defined as involving conscious intellectual activity like thinking, reasoning, etc.. "Cognition" is a cognitive mental process; therefore, human cognition is the cognitive mental process of a human being. However, for this study the focus is on human performance of a specific task, not on inner, complex actions of the brain. Therefore, in this work, cognition is the cognitive mental process of a human being required to complete a task. As noted earlier and further explain in section 2.1, this work draws upon the research that the human brain can only detect a finite number of objects and that human cognition is limited (Misra and Stokols 2012). Therefore, in this work, performance is measured as a manifestation of the inner cognitive workings of a person. The better the performance of an individual, the better the cognitive ability of said individual.

Focusing on the performance of the human operator, there are two areas that will be evaluated for this body of work. First, is how well the human operator can detect and identify a specific entity on their computer. The rationale for this is that the EMS data collected from the sensor must be represented in a medium understood by a human operator, i.e. the computer screen. The operator's performance to detect and identify the specific entity will be measured utilizing the Targeting Task Performance Metric (TTPM) (see section 2.8) that focuses on the human visual system (eyes and brain) (Hixson et al. 2004; Vollmerhausen 2004, 2009; Preece et al. 2014). Therefore, the performance of the human operator to detect and identify a specific entity on a computer screen (that has been transmitted to it from an optical sensor) will be measured by performance of the eyes and brain of the operator to detect that object.

Since this work will incorporate more than one human operator, the second assessed task performance will focus on how well the operator can communicate the location of a specific entity, that their optical sensor has detected, to another human operator that will use another optical sensor to identify the entity. Evaluation of this task will incorporate different cognitive mental capacity metrics titled Task Load (TL) and Working Memory (WM). This communication performance will also include the Message Quality (MQ) between these operators. Combined, these metrics provide a predictable estimate on the performance of communicating a geographic location to another human (de

Visser et al. 2010; de Visser and Parasuraman 2011; Ahmed et al. 2014). This will be further examined in sections 2.5 and 2.7)

Added to complexity of communicating cognitive ideas are the errors or differences between where the entity actually exists, at a specific point in time, and what the machines and humans estimate that entity to be located. These errors need to be incorporated into this whole process of detecting, communicating, and identifying this specific entity (Shi 2010; Caers 2012). These errors, or "uncertainty in a geographical location," are inherent in the technology and estimations that result from the reductionism of taking the infinitely complex geographical world and creating an abstraction of the real world through digital or data modeling methodologies (Zhang 2002; Hüllermeier et al. 2010). It is an additive effect resulting from technology (e.g. calibration of optical sensors) to the error in the human operator's estimation that increases depending on the complexity of the system (Heuvelink 1998; Karssenberg and De Jong 2005). For the purposes of this research, this Geographical Location Uncertainty (GLU) will propagate throughout the whole system, with each error being an additive addition to the overall uncertainty that will degrade the performance of finding and identifying a specific entity. GLU will be further discussed in section 2.9.

Figure 3 visualizes the different aspects of the problem for this research. Compared to Figure 2, an additional platform equipped with a different optical sensor, with corresponding human operator, are added to the overall system.

GLU is inherent within all aspects of the system, from the technological sensors to the human operators. As laid out in this figure, error is also inherent in how people communicate locations and directions to one another and this is evaluated between the two operators (Heuvelink 1998; Bergstrand et al. 2016). Within the operator, they visualize the entity through the technical system and this performance is measured by TTPM. TL and WM are ingrained within each operator that will impact their performance in communicating the GLU laden entity location. Between the two operators, MQ and GLU are communicated, impacting overall performance of the system; therefore, and to simplify, this work provides a unique way to evaluate the performance of a system (and thus incorporate it into a system of systems) by not only testing the technical parts of the systems but also incorporating the capabilities and limitations of the human part of the systems that not only operate but draw understanding from the information or data of the system.

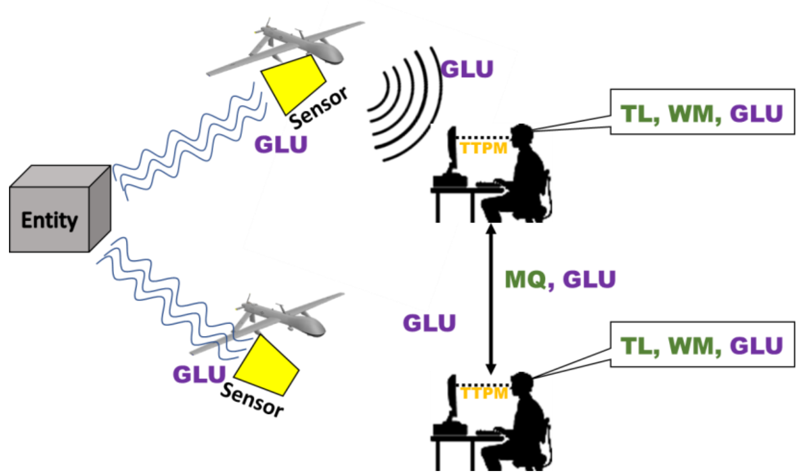


Figure 3 Graphical representation of the Problem for this Research

1.3. Connecting the Problem through Situational Awareness

A basic problem being evaluated in this research is determining how much the operator knows what is going on through the sensor. "Knowing what is going on around you" or 'having the big picture" is defined as Situational Awareness (SA) (Jones 2015). Current research has moved past studying the individual and into more complex systems of interacting humans and technical agents. In Stanton et al.'s (2006) research, SA is defined as:

> activated knowledge for a specific task within a system…. [and] the use of appropriate knowledge (held by individuals, captured by devices, etc.) which relates to the state of the environment and the changes as the situation develops. (Stanton et al. 2006)

This change is correlates to the ever-increasing incorporation of technology into a person's life. SA research's focus has evolved from basic human factors that emphasized individuals to incorporating whole systems of actors (human and non-human) (Hutchins 1995; Button 1997; Rasmussen 1997; Leveson 2004; Walker 2009; Wilson 2012). As an academic concept, SA research contains the various models and methods that assist researchers and practitioners with describing how individuals, teams or systems develop SA. Additionally, it provides a methods and measurements of assessing the quality of SA during task performance (Salmon et al. 2013).

Since the premise of this research is the awareness and understanding of what is going on around an agent, team or system, referenced research focuses on the concept of ‘situation focus’ and measuring the objective ground-truth verse an adjudicated ‘awareness.’ As a methodology, this is an appealing cause (situation) and effect (awareness) way of evaluating this ‘ground truth’ principle (Stanton et al. 2017). Correlating ground-truth and the level of awareness within a given situation tends to presume a ‘mapping of the relevant information in the situation onto a mental representation of that information within the [individual]’(Rousseau et al. 2004). This body of work is an examination into narrowing the gap between ground truth and the mental representation of an entity’s location. Looking at this problem through a SA methodology helps extract and explain all relevant factors that narrow this gap, including Geographical Location Uncertainty (GLU).

Current research into SA examines how the whole system operates and that all parts of the system hold their own form of SA – both human and technological agent. Each part presents and communicates a replication of the ground truth. This theory was expanded over the last decade and refined into the Distributed SA (DSA) model by Stanton et al. (Salmon et al. 2008, 2009, 2016; Neville and Salmon 2015; Stanton et al. 2015; Stanton 2016). This is further examined in section 2.4.3. In context to this body of work, this is the basis of propagating geographical location uncertainty throughout the system but also the difficulties of communicating SA. Within DSA, the overall system’s situational awareness is dependent upon the network and the communication of the information upon it. Additionally, each node of this system (or network) have distinct views and relationships (Stanton et al., 2006; Stewart et al., 2008; Salmon et al., 2009; Walker et al., 2010). Human operators have their own view of ground truth and so does the platforms and their sensors. Combined, there exists a formal or informal process to negotiate a collective notion of ground truth that evaluates all views of the system.

An example of DSA occurs within the cockpit of a fighter jet (or commercial aircraft). A pilot, controlling the aircraft, understands the situation from their viewpoint, while the co-pilot has a slightly different view of the same situation. This is mainly based on the different tasks that each agent is executing. Additionally, and incorporating the technical part of this SA, the aircraft's systems have yet another view and of the situation based on what each sensor is designed to monitor. Taken as a system, each part (sensor or pilot) contributes to the overall situational awareness of the system as a whole. The pilot communicates their plan of action. To assist in this endeavor, the co-pilot updates or reads the outputs from the systems of the aircraft such as the airspeed and altitude. The sensors themselves function within the parameters of their design and measure certain phenomena around the aircraft. The overall key to DSA is the interconnectivity of these various views in providing the appropriate information to the right agents at the right time (Stanton et al. 2017).

1.4. Significance of this Research

Arnheim (1997) stated in this book "Visual Thinking," a precursor to the field of visual analytics, that research in this area searches for a way to augment the strengths of human visualization and cognition with the power of computer technologies. Additionally, Johnson and Hanson (2011) stress that the goal is to identify the best automated processes for the task at hand, estimating limits that can't be further automated, and then develop a tightly integrated solution that adequately integrates the top automated processes and human performance methods into a cohesive methodology. Within this work, the application of converging the best automated technological processes (computers) and human performance outcomes, within an interconnected system of system, is tied to the task of finding and identifying a specific entity. This converges with a segment of visual analytics that researches how augmenting human beings with computers improves their ability to use visual-based sensors to find something or someone (Keim et al. 2008).

Research on DSA models or team functionality has been conducted on different configurations of people and technology in many fields. Several studies cover military and commercial aircraft and their crew. They have focuses on how the pilot, co-pilot and the aircraft's sensors have differing views of the same situation and how this effect's the overall performance of the entire system (Stanton et al. 2017). Other research, emphasizing performance and how corresponding facts impact it, focused on many contexts, including military settings (Endsley, 1993, 2015; Stanton et al., 2006; Salmon, 2009; Salmon et al., 2009; Stanton, 2014) transportation (Ma and Kaber 2007; Salmon et al. 2008b, 2014; Stanton and Salmon 2009; Golightly et al. 2010, 2013; Walker et al. 2013), process control (Salmon et al. 2008b; Stanton et al. 2009; Sneddon et al. 2013), and emergency services (Blandford and William Wong 2004; Seppänen et al. 2013). Other studies have evaluated other domains that contain high levels of technology and safety requirements (i.e. aviation, aerospace, chemical and petroleum process industries, healthcare, defense and nuclear power). Incidentally, it was the research conducted in these fields on improving conditions and performance that lead to the impetus of SA not only for human teams but also non-human agents (Stanton et al. 2010; Hollnagel 2014).

The significance of this research is the creation of a DSA model for a specific task, under the aspects of visual analytics, that combines the measurements of technological performance and human performance in a distributed system that is degraded by geographical location uncertainty. The task of this system is to find and identify a specific entity in a complex, urban landscape with optical sensors. The DSA model fits the problem set in this body of work because of the research conducted determining if a relationship existed between DSA and task performance. These experiments examined the conversations teams exchange when performing tasks and calculated a positive relationship between DSA and the teams' performance (Sorensen and Stanton 2013). This same positive relationship was also found in other high-fidelity, training environments for search and rescue crews and also within other military units (Rafferty et al. 2013). Ultimately, this presents evidence that SA is useful in predicting performance (Patrick and Morgan 2010; Bleakley et al. 2013; Golightly et al. 2013). The scientific contribution of this work is a DSA model incorporating research from the social sciences into a more exact science of technological detection of an object. It is unique due to the inclusion of many facets (geographical location uncertainty, human communication performance, human visual system, and mental constraints) to create a tool to predict performance for the specific task of detecting and identifying a specific entity in a complex environment.

1.5. Motivation

As indicated previously, the focus on this research is on creating a novel DSA model that maximizes processes through the combination of people and technology. The work in this paper also evaluates a sensor system consisting of platforms equipped with optical sensors to human operators that are making decisions based off of the data collected by these sensors. Evaluated research on sensor systems in this work replicated the human part of the system as a "black box" in order to minimize the complexity and variability of that part of the overall system (Vollmerhausen 2009). However, a vast majority of tasks are conducted in teams or with individuals that have to constantly coordinate with another individual which leaves an important aspect of task performance unaccounted for in these simulations or evaluations (Ahmed et al. 2014). Additionally, emergency response teams, law enforcement, and search and rescue squads are dependent upon good communications to accurately and quickly find a person in a complicated and dynamic environment (Bergstrand et al. 2016). What current research indicates is a need for reliable modeling that incorporates different capabilities to teams might be able to predict future performance (Blasch et al. 2015). These models will then provide more information for decision makers when purchasing advanced communication systems, training for their teams, or push for changes in organization structure, procedures, and processes.

This leads to the motivation for this work. Keim et al. (2008) describes a segment of visual analytics that researches how augmenting human beings with computers improves their ability to use optical sensors to find a specific entity. Opening the “black box” of the human operator incorporates complexity into this research but provides a critical addition to this segment’s body of research on team task performance within a DSA model. It will provide examples of human operator models incorporating differing aspects of cognition into their measurements of task performance.

1.6. Contribution

This work provides a DSA model that can be used in the fields of remote sensing, system and team performance analysis, and also in the acquisition of new technologies. It distinctively combines exact technological models of specific aerial vehicles and optical sensors with human performance models. These human performance models incorporate mental capacity metrics such as Task Load (TL) and Working Memory (WM) to measure the cognitive ability of a human operator on a particular task. Then, it incorporates these metrics into a human communication model that utilizes a Message Quality (MQ) metric to determine task performance. Research from this work will support a DSA model that predicts the task performance of detecting and identifying a specific entity with two different sensors. It is based not only on sensor parameters but on the cognitive capabilities of human operators and how well they communicate between one another for a particular task. Conclusions from this work will provide further research on situational awareness and provide an example of how geographical location uncertainty impacts a DSA system's ability to locate an entity – especially if location is critical to task performance. As stated by Ahmed et al. (2014), tasks are completed by teams and more research on evaluating a team's performance on a job is builds upon the related bodies of science. Therefore, this work provides an assessment tool for any organization in which teams, communication, and time are important to the competition of their task.

Since aspects of situational awareness focus on ground truth (the exact location in an environment) and how close an entity is to that ground truth with their own estimation, GLU provides a level of measurement between an exact measurement (ground truth) and an estimate. Combined together, these factors provide the scientific community a unique model that can be used to predict task performances, on a narrow set of tasks, providing information on the interaction between technological systems and team performance.

1.7. Intended Audience

This work is intended for four primary audiences: operators, the forensic, acquisition, and GeoInformation Science communities. This new task performance model will enable these communities to incorporate SA and team performance into their events. Additionally, this incorporation allows them to replicate tasks and gain results that are more comparable to real-world assessments. This research contributes the most to those operators and organizations where location and time are utmost important to their primary tasks. For these organizations, this work provides research on the effect that communications (message quality) and situational awareness has on their primary task. Additionally, it presents potential technological framework that automates this process as much as possible (in an aided manner – not automatic). Especially when teams don't have time to train on communication skills. The forensic community can utilize this model in accident investigations to provide better insight into how poor communication between human operators and the technological agents created the situations that led to an accident where a specific location is in question. This could be anything from the aviation community to nuclear reactor operation centers. If specific problems are determined, these can be better defined and changes can be implemented to improve the safety in many different industries. For the acquisition community, the results of this work provide new evaluation parameters to quantify the effectiveness of new technologies if using an existing team performance for a specific task. GeoInformation science researchers and other data scientists will find interest in the results due to another method of incorporating two scientific fields and providing another aspect of remote science and human performance.

1.8. Chapter Roadmap

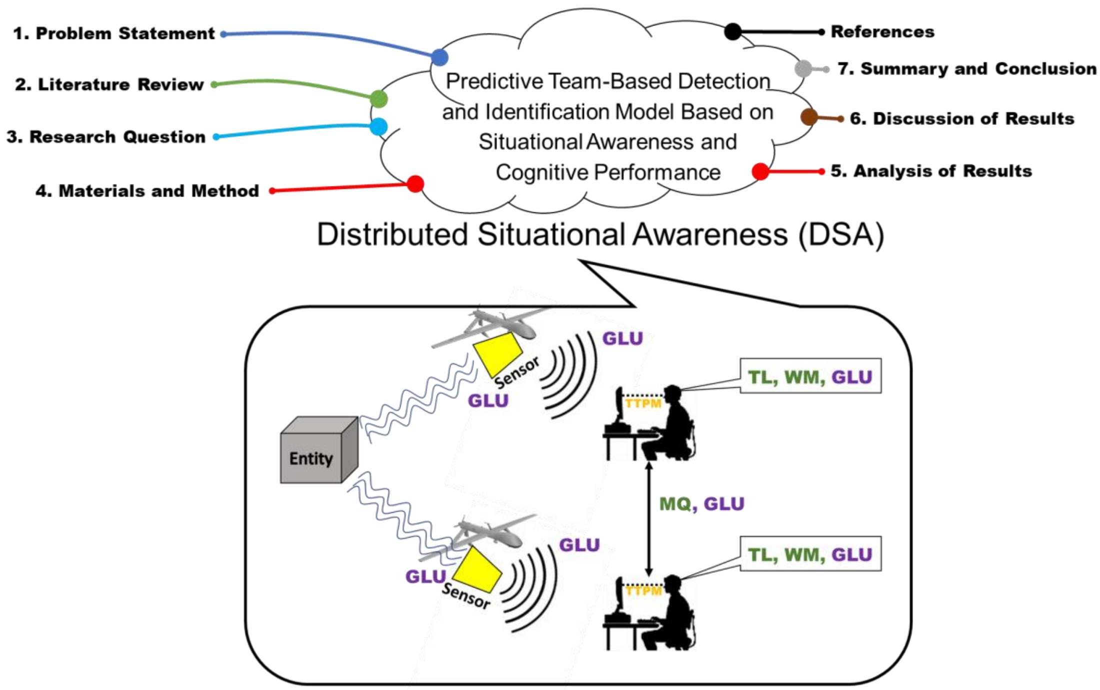


Figure 4 Roadmap for this work
DSA = Distributed Situational Awareness (Section 2.4)
GLU = Geographical Location Uncertainty (Section 2.9)
TL = Task Load (Section 2.5)
WM = Working Memory (Section 2.5)
MQ = Message Quality (Section 2.5)
TTPM = Targeting Task Performance Metrics (Section 2.8)

In chapter one, the problem for this work is defined and lays out its contribution and potential impact to the larger science community. Chapter two provides a summary of visual analytics, its sub-scientific fields and explains the methodologies of finding and identifying an unknown entity in a complex environment. The core scientific theory of this work, Situational Awareness, will then be explained, moving into the final theory of Distributed Situational Awareness and how it impacts this work. The sub-components of this work will then be discussed in greater detail. Human cognition through team performance assessments, and its relationship to training, will be explained along with the central theory to this work – targeting task performance metrics. Geographical location uncertainty will be explained and further discussed as to its relevance to this work. Additionally, relevant electronic optics utilized in this experiment will be defined, explained, and discussed in its importance to this work. Finally, the Aided Target Recognition theory, with technological examples will be defined and discussed.

Based on the literature review, the research question is further defined in chapter three with the main hypotheses for this work. Chapter four explains in detail how the experiments will be performed. The role of modeling and simulation in the experiment will be defined, and how it will create the data required for further analysis. The simulation engine, FOCUS (Fusion Oriented Command, Control, Communications, Computers, Intelligence, Surveillance, and Reconnaissance (C4ISR) Utility Simulation will be explained, along with its current validation as an assessment and analysis tool for this experiment. The overall experiment will then be described in greater detail. How the entities in the simulation are replicated, to the terrain utilized will be explained. The next step then explains how the components of the experiment will be replicated and analyzed within FOCUS.

Chapter five will provide analysis of the results from the experiment and the data pulled from FOCUS. This includes determining significant differences and correlations of the data outcomes. Chapter six will discuss these results in more details to include issues to address concerning the processes chosen for this work and also the impacts of what the results indicate. Finally, the last chapter will provide a summary of this work and conclusion, with last comments on potential future work that can be conducted based on the results of these experiments.

2. LITERATURE REVIEW

This chapter will define and present the research on the main topics for this work. It will begin on the defining the interaction between human visualization and computing power foundational to this work. Research will then be presented that ties together the aspects of detecting and identifying a target, not only individually, but through team performance. Different aspects of this task will be broken down and defined to provide context and parameters paramount in this work. It will end in describing the optical sensors that provide the data needed for the experiments and overall assumptions foundational to this paper.

2.1. An Overview of Visual Analytics

Visual analytics is a relatively new term and was first used when the book "Illuminating the Path" was published by Thomas and Cook (2005). However, the idea, research, and approaches that fall into this research area emerged much earlier. It is defined as the study of human cognition and electronic data processing, and its overarching goal is to develop a better basis of understanding on the methods, technologies and practices that exploit and combine the strengths of human and computer processing (Keim et al. 2008). Visualization is "the means through which humans and computers cooperate using their distinct capabilities for the most effective results"(Andrienko et al. 2010). Many research areas utilized this methodology in information visualization, GIScience, geovisualization and data mining long before 2005 through the use of novel maps and functionality (Slocum et al. 2001; MacEachren et al. 2005; Andrienko et al. 2011b). Since 2005, research has attempted to establish visual analytics as a specific scientific discipline "to consolidate the relevant research that has been conducted within different disciplines" (Andrienko et al. 2010). GIScience and geovisualization can assist in this process(Slocum et al. 2001; Crooks et al. 2013; Croitoru et al. 2015).

For this research, the focus is on the combining the visual components of the human being and computers. Humans utilize their biological sensors (eyes) to send data to the processing center (the brain) which then uses it to analyze the data and replicates a visual or understanding of its surroundings based on the data and processing capabilities. As we progressed over the eons, the advent of computers and an increasingly technological society have stressed our capacity to handle all of the visual information that assaults our senses. Research by Misra and Stokols (2012) indicates that we are limited by our biology (the human brain) in how much data our human visual system and organic cognition abilities can handle in a specific amount of time. Research has termed this experience, when a person cannot process the information received due to the large amount of incoming data, as "information overload" (Lipowski 1975; Sweller 1988; Van Zandt 2004; Misra and Stokols 2012). When an individual perceives they are suffering from an information overload problem, a form of psychological stress occurs which effects their ability to conduct work (Entin and Serfaty 1999; Misra and Stokols 2012). Resulting in this stress is a reduction in working memory or ability to balance actionable items within a person's mind. This ultimately leads to a decrease in performance (Engle 2002; Huang et al. 2009).

For this work, the premise is that the human brain can only detect a finite number of entities and then even less if it has to identify a specific one. This extra step in identification requires additional cognitive resources; thus, reducing the finite capability to detect additional entities. Variables like terrain complexity and other outside stimuli will affect this finite number. A couple of entities might not be a problem, but an urban environment full of different entities would overload the capacity of the human brain – even several people working together. Answering the question of "how many is too much" will depend on the complexity of the environment and the difficulty of the task.

Therefore, the problem isn't only acquiring data but also identifying methods and models that can turn this information into reliable, provable, and actionable knowledge (Kerren et al. 2011). However, past research provides evidence that technology can't fix this problem alone. The system must be measured holistically, taking into account the human and non-human entities that create it (Keim et al. 2008; Stanton et al. 2017). Proper analysis provides a framework to compartmentalize the complex problems and lets us face the problem of understanding and "analyzing our analysis" to determine if low cost processes and procedures can be incorporated into complex data analysis instead of costly technological solutions (Andrienko et al. 2011a). The overarching vision of visual analytics is to turn information overload into an opportunity with the goal being to make data or information process more transparent to analytic techniques (Thomas and Cook 2005). For this work, the technical aspects will be examined in section 2.12 and also within the the second hypothesis in section 3.3.

Visualizing these procedures and processes is key to this analysis – regardless of the medium in which a human being receives the information. Visualization becomes the instrument of a semi-automated analytical process, where humans and machines complement their respective distinct capabilities and limitations for the most effective results (van Wijk 2005). Being highly interdisciplinary, visual analytics combines various related research areas such as visualization, data mining, data management, data fusion, statistics and human factors science (among others). Overall, the goal of this merging of other disciplines is the creation of tools and techniques to enable people to better synthesize information in order to derive increased insight into the complexity of data (Thomas and Cook 2005). However, visual analytics is more than just visualization. It is an integral approach to decision-making, combining visualization, human factors, and data analysis (Keim et al. 2008; Liu and

Fuhrmann 2018). The challenge is to identify the best automated processes for the analysis task at hand.

2.2. Visual to Video Analytics

With the proliferation of cameras, from individual ones that people wear like helmet cameras (https://youtu.be/fXfBqxlp0mw) or police body video cameras (Headley et al. 2017) that provides endless hours of video. To those working to support a larger system for security or surveillance reasons (Chen et al. 2016), also continuously adding to the vast ocean of video data that is unstructured or difficult to analyze. Some of the video is downloaded at a later time or continuously uploaded into social media sites for the user and their friends to view in either near real-time or at a later date. This creates a requirement to determine processes or procedures to better analyze these large volumes of video data (Choudhary and Chaudhury 2016).

Video analytics is an industry term for the automated extraction of information from video for a variety of purposes. It is a sub-set of the larger field of visual analytics and just like its parent field, it focuses on applying a combination of imaging, computer vision, pattern analysis, and machine learning to apply upon real-world problems. These problems can be determining traffic congestion based on tracking vehicles (Coifman et al. 1998) to analyzing how people transverse different obstacles in an urban setting (Favorskaya 2016). Applications also include detection of suspicious objects and also improvement of security operations (Hu et al. 2004; Choudhary and Chaudhury 2016). For law enforcement, several applications are license plate recognition and traffic analysis for intelligent transportation systems (Gagvani 2009). Video analytics is important to this work since the sensors utilized for its experiments are optical sensors that are continually capturing optical images that are in size from several megabytes to gigabytes – depending on the size of the image. This creates a problem of transmitting and analyzing a large volume of video data.

The main difference between visual analytics and video analytics is with the requirement for sequence of pictures in temporal order to provide context and better understanding of visual scenes. Again, this is why this subset of visual analytics is relevant to this work due to the full motion video and wide area motion imagery optical sensors used in this work. Similar to web analytics, which is the study of deriving intelligence from web logs, video is treated as a data source and through different processes under video analytics attempts to extract meaningful information from it. As with most analytical processes, most of the output is generally quantitative and structured information that summarizes some feature related to the content of video. Therefore, it is also called video content analysis (VCA) or video intelligence (Gagvani 2009).

2.3. Methodologies in Finding and Identifying an Entity

Referring back to the “Yellow Taxicab” problem (see section 1), and for this work the entity that the analysts and sensors are searching for in an urban environment is a specific, yellow taxicab. Taken as a distinct and unique entity, this vehicle stands out from the background due to many distinct characteristics, all with physical properties that can be measured by sensors. In this section, a simple methodology developed by the U.S. military (United States Joint Forces Command 2007) to differentiate between entities and the background will be described. It provides a process that military analysts utilize to detect and identify entities through the remote sensing of optical sensors and can be explained in three steps:

- Find – actually finding and identifying the entity with remote sensing assets (e.g. yellow taxicab or finding lost hikers on a mountain).
- Fix – this is the location (current or future) of the desired entity (e.g. where in the city is the taxicab at a specifc time or a location of lost hikers is determined through remote sensing).
- Track – entity is under constant observation or surveillance (e.g. following the yellow taxicab throughout the city to determine where it goes, stops, picks up or drops off – providing continuous updates).

These steps are important in this work because it describes an official methodology to evaluate accuracy, required time to detect and identify, and incorporates skills levels of the human operators into these three steps. It also provides the framework for the experiments utilized in this work.

2.3.1. Characteristics Impacting Entity Detection

Every entity (and every yellow taxicab) has unique characteristics which effect how different sensors can detect it. These characteristics form the basis for the step of “find.” The U.S. military (United States Joint Forces Command

2007) provides a concise explanation and description for the three categories of characteristics by which entities are detected:

1. Physical Characteristics. The physical features that describe and physically define an entity. Examples include location, shape, size, number, dispersion, reflexivity, electromagnetic signatures, and mobility characteristics (moving, stationary, or fixed).

2. Environmental Factors. These factors describe how the environment affects the entity. Effect of weather, terrain, proximity to items that effect the sensor's ability to properly collect data from the environment all impact how it will be acquired and detected.

3. Time-Sensitivity. Prior decisions might make the entity a priority or it commits an action that requires immediate action. An example is if a hiker gets hurt and needs immediate medical attention. This puts the entity at a higher priority and might require addition assets to find and fix and/or track the entity.

From these characteristics, analysts and the sensors they utilize are able to acquire an entity and then, technically, be able to properly detect and identify a particular entity.

For this work, categories 1 (physical characteristics) and 3 (time-sensitivity) are of importance. Category 2 (environmental factors) can be of importance but in order to simplify the experiment, all environmental factors will be removed. This will allow results to focus on the methodology and not environmental factors that might be circumstantial. Sensors utilized in this work will be optical and will evaluate entities by their physical characteristics, or those characteristics that reflect aspects of the electromagnetic spectrum. Additional information on these sensors is provided in section 2.10. Additionally, detecting and identifying the entity is time sensitive since the targeted entity will be moving from a starting point to a destination and it is only during this movement that the entity can be detected by the sensors. Also, the time of how long an entity is tracked will be used to evaluate the differences between the dependent variables in the experiment.

2.3.2. Considerations for Entity Tracking

In general, tracking of a moving entity (like a yellow taxicab) requires recognizing and then locating the entity in a scene, determining its motion and projected pathway, and then following that entity as it moves through the sequence of image frames (Hwang et al. 1992; Nakano et al. 2016). Tracking of this entity is defined in the science of video analytics since the sensors utilized in this work are continuously capturing optical images over a specific time period. The detection and tracking of desired entities in images corrupted by noise, clutter, illumination and other three-dimensional artifacts, poses a very complex problem and demands sophisticated solutions using pattern recognition and motion estimation methods (Pantrigo et al. 2010; Cao et al. 2012; Chen et al. 2016; Lipton et al. 1998). The challenges become even more complicated if there is more than one entity in the scene and simultaneous multiple entity tracking is required.

For this work, a team will be measured on how well they track a specific entity (yellow taxicab) within the complex urban environment. Detection and identification of this independent moving objects through the images produced by optical sensors is independent variable within the experiments comprising this work. Therefore, the sensor properties have to be incorporated into the experiments along with the challenges resulting from tracking many different images and covering a larger field of view. This creates additional challenges in detection and tracking (Bal and Alam 2005; Dawoud et al. 2006). Of the various approaches in detection, recognition, classification and position estimation of targets from images, researchers have investigated several methods including both Matched Spatial Filter (MSF), base correlators, and joint transform correlators (Mahalanobis 1997; Mahalanobis and Muise 2001; Alam and Bal 2004; Bal and Alam 2005; Dawoud 2005; Alam et al. 2003). However, the application of MSFs or their variants for imagery is very limited; although those have been used for the simulated and real synthetic aperture radar (SAR) and light detection and ranging (LiDAR) imagery.

In order for a target to be tracked, it needs to be continuously detected by a sensor and then followed through subsequent images by a human analyst or other technological means. This continuous detection creates a “track” or path that is created as the location of the target is geo-located over a set iteration of time (e.g. 2 seconds). Researchers in the past would look at individual images and manually mark and track an object on a map; however, today’s technology, within constrained parameters, enables computers to find and track these objects (and multiple objects) much faster than a human in certain conditions (Alam 2007). For humans, most of these steps are done internally to the human visual system (HVS), but the process has been examined and documented and simplified to a two-step process. Alam (2006) developed this process and have conducted several research studies on its validity. The first of two steps of this process (which can occur in real-time) is detection, which involves correlating the input scene with all detection filters (one for each desired or expected target class) and combining the correlation outputs. In the second step, a predefined number of areas of interests (AOIs) having the expected size of target images are selected based on the areas having higher correlation peak values in the combined correlation output. To ensure that all desired or expected targets are included in the AOIs, their number should be at least three times higher than the number of expected targets (Bhuiyan et al. 2014). Within the final part of step two, classification filters are then applied to these AOIs and target types along with clutters are identified based on a distance measure and a threshold. Moving target detection and tracking are accomplished by following this technique for all incoming image frames by applying the same filters (Alam 2006, 2007; Islam and Alam 2006; Alam and Bhuiyan 2014). Due to today's computing power, this processing can occur at near real-time. However, the success of the method depends on how fast the transmission of an image is to the processor and then to a human analyst.

2.4. Situational Awareness (SA)

At the most basic level, SA could be described simply as ‘knowing what is going on around you’ or ‘having the big picture’ (Jones 2015). Others have described it as the capability of actors (mostly people, but not limited to only them) to interact and connect with their surrounding dynamic environment (Dogan et al. 2011; Yu et al. 2016). Initial research on SA focused on the individual and used the term ‘situational awareness’ as defined by Endsley (2015).

> Situational awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and a projection of their status in the near future (Endsley 2015).

Research over the decades has led to the evolution of the definition into teams with current research focusing on more complex systems of interacting humans and technical agents. Within this body of evidence, Stanton et al. (2006) defines SA as:

> activated knowledge for a specific task within a system…. [and] the use of appropriate knowledge (held by individuals, captured by devices, etc.) which relates to the state of the environment and the changes as the situation develops (Stanton et al. 2006).

This new perspective of a systems of systems moves from the older view of the cause and effect logic of individual models that has been rooted in cognitive psychology. Incorporating non-human agents (technical agents) has radically increased the controversy of SA definitions within this academic community (Endsley 2015). However, as technology becomes more ingrained in everyday life and how it effects people's interactions with their environment, its ever important and relevant to infuse current and future research concepts with these systems of systems perspectives, especially with growth of advanced automations and the emerging field of artificial intelligence (Hancock 2014, 2017).

Due to the rapid growth in definition and utilization of SA, some professions and academic disciplines refer to SA as the process of interchanging information between people of what resides in their heads (Fracker and Logue (Goerge E) Inc. Montoursville, PA 1991; Sarter and Woods 1991; Endsley 1995) or specifically their brains (Endsley 2015). Research in this area is increasingly incorporating entire socio-technical systems and how they interact with an operational or more realistic environment. As noted before, its focus has evolved from basic human factors that emphasized individuals to incorporating whole systems of actors (human and non-human) (Hutchins 1995; Button 1997; Rasmussen 1997; Leveson 2004; Walker 2009; Wilson 2012). As a theoretical concept, SA research contains the various models and methods that assist researchers and practitioners with describing how individuals, teams or systems develop SA. Additionally, it provides a methods and measurements of assessing the quality of SA during task performance (Salmon et al. 2013).

2.4.1. The Role of Ground Truth

At a higher level, SA is perceived as the awareness and understanding of what is going on around an agent, team or system (Jones 2015). A perceived and viewed environment is not static and is continually changing, demanding the attention the agent. Within research on this topic, effort is devoted to the concept of ‘situation focus’ and measuring the objective ground-truth verse an adjudicated ‘awareness.’ As a methodology, this is an appealing cause (situation) and effect (awareness) way of evaluating this ‘ground truth’ principle. However, upon closer evaluation, there are several important subtleties that need to be addressed (Stanton et al. 2017). Correlating ground-truth and the level of awareness within a given situation tends to presume a ‘mapping of the relevant information in the situation onto a mental representation of that information within the [individual]’ (Rousseau et al. 2004). This mapping of a ‘mental representation’ can be split into two aspects of ‘awareness’. First, the ‘mental representation’ consists of structured ‘relevant information’ and that SA depends on the contextual interconnections between discrete elements. Second, as described by Endsley and Garland (2000), it is also an ‘abstraction within our minds’ which reflects another or the second aspect of awareness - its hypothetical nature depending upon the circumstances (Bryant et al. 2004).

In order for agents to make better decisions and improve their performance, SA needs to provide them with ‘explanations for all attendant facts’ (Reber 2009) and how these facts or attributes are affecting the performance of the agent. Several studies have focused on capturing these performance and corresponding facts. This research includes military settings (Endsley, 1993; Stanton et al., 2006; Stewart et al., 2008; Salmon, 2009; Salmon et al., 2009; Stanton, 2014) transportation (Ma and Kaber 2007; Stanton and Salmon 2009; Golightly et al. 2010, 2013; Walker et al. 2013; Salmon et al. 2014; Fuhrmann et al. 2015), process control (Salmon et al. 2008b; Stanton et al. 2009; Sneddon et al. 2013), emergency services (Blandford and William Wong 2004; Seppänen et al. 2013), and location-based social networks (Crooks et al. 2013; Liu and Fuhrmann 2018). Additionally, these provide explanations on the outcomes of 'lost' SA and the impact this has upon performance, especially when it is first gained or later regained (Stanton et al. 2015).

2.4.2. Sociotechnical Systems (STS)

Basically, deconstructing the word "sociotechnical" defines it as a combination of people ('socio') with technical elements. These two elements then interact in an activity that supports a larger system or organization. "Socio" also indicates that teams and teamwork is one core of the STS concept with technology comprising the other core. However, STS is more than merely teams, it involves multiple stakeholders that govern distinct policies, rules, and culture and the systems that they utilize. A foundation of the STS concept is that people and systems cooperate in multifaceted, non-deterministic and often in non-linear and non-additive ways. This complexity then requires a high level of 'joint optimization' in order to be successful (Walker 2009). As shown in other research, this complexity is indicated in other domains that contain high levels of technology and safety requirements (i.e. aviation, aerospace, chemical and petroleum process industries, healthcare, defense and nuclear power). Incidentally, it was the research conducted in these fields on improving conditions and performance that lead to the impetus of STS (Hollnagel 2014).

As products and services become more complex and networked, the STS concept increases in relevance for a greater audience (Walker et al. 2008). In research conducted to date, studies upon closely connected, interactive complexities (especially in accidents) has led to unexpected results and outcomes of how the systems succeeded or failed (Perrow 1999; Stanton and Walker 2011; Salmon et al. 2013; Croitoru et al. 2015). An impactful outcome of this research indicates that even though these systems are complex, they are non-reductive. Due to their interconnectivity, they cannot be simply disaggregated into smaller, more manageable elements as research has shown with simpler linear systems (Liang et al. 2005; Walker et al. 2010). This has shown that traditional reductionist approaches based in experimental cognitive psychology cannot be easily utilized to explaining SA. STS' more systematic way of explaining SA is more appropriate for the complex, technological environment of today (van Winsen and Dekker 2015).

2.4.3. Distributed Situational Awareness (DSA)

Evolving SA from teams into systems began with the work of Artman and Garbis (1998). Their research moved from focus on individuals to how the whole system operates and argued that not only people hold SA but all the parts of the systems hold their own form of SA. Each part presents and communicates a replication of the ground truth. This was a change to current research because their model focused on the interactions between people (and artifacts or machines) instead of a person's individual cognition. This theory was expanded by Stanton et al. (2006; 2009; 2010; 2014; 2015; 2016; 2017) and associates over the last decade and refined into the Distributed SA (DSA) model. Within this model, SA is based on the interactions between agents (human or technological) within a collaborative system. Additionally, its popularity in research has grown over the last decade due to the ever-increasing inclusion of technology into society (Neville and Salmon 2015; Hancock 2017).

For this work, the DSA encompasses the entire aspects of the experiments that were run. As indicated in Figure 5, the DSA connects the human analysts and the sensors and their platforms, with each holding their own SA and estimate of ground truth. When communicated, different aspects of SA from other parts of the system interact to form a new estimate of SA that is then propagated through the system to the next node or part.

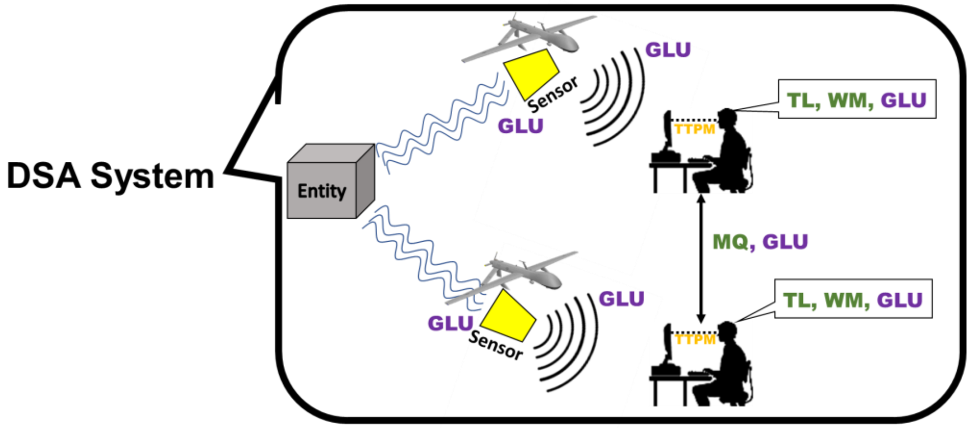


Figure 5 Distributed Situational Awareness System utilized in this work.

Due to the dynamic nature of this information, it needs to be constantly monitored if it is to be understood, especially if there are changes in the task, environment, and other interactions (both social and technological) (Liang et al. 2005; Patrick et al. 2006; Duckham et al. 2007). As part of the model, DSA focuses on one task at a time and the knowledge associate with that task. An agent within the network is the owner of the task and the other agents and information is networked together by the information or knowledge in order to complete that task (Seeley et al. 2012; Crooks et al. 2013). Each node within this network turns on or off depending on the task, environment, or interactions required at a given time. Ownership is not of importance in this system, but what is vital are the pathways and unfettered flow of information. Due to the dynamism within this network, it is extremely difficult, if not impossible, to re-create with reductionist, linear approaches. Therefore, the necessary theoretical foundations and tools to explore the nonlinearity within this complex sociotechnical model can be found within the study of systems (Walker et al. 2010; Crooks et al. 2013; Croitoru et al. 2015; Liu and Fuhrmann 2018). An example of evaluating DSA theory was conducted during a large-scale U.K. Army field trial of a new mission-planning and battlespace management system and produced satisfactory results (Stanton 2009). Additional research was conducted to determine if a relationship existed between DSA and task performance. These experiments examined the conversations teams exchange when performing tasks and calculated a very strong positive relationship ($r = 0.923$, $P < 0.001$). between DSA and the teams' performance (Sorensen and Stanton 2013). The same positive relationship was also found in other high-fidelity, pre-deployment training environments (Rafferty et al. 2013). Therefore, research has determined there is a strong relationship between DSA and team performance on tasks. Ultimately, this presents evidence that SA is useful in predicting performance (Patrick and Morgan 2010; Bleakley et al. 2013; Golightly et al. 2013).

2.5. Measuring Human Cognition Through Team Performance Communications Assessment

As noted earlier in this work, when most performance evaluations of sensor systems are conducted, the human part of the system is usually treated as a "black box," with the complexity of the operator/analysts reduced to a simple number. A rationale for this simplification is networked systems are very intricate and not completely mapped out and, additionally, difficult to predict (McKendrick et al. 2014). Additionally, creating experiments is all about reducing variables and most human beings are full of contradicting skills.

To address this “black box” issues, numerous research studies have been conducted, mostly in the fields of human factors or ergonomics. These studies cover the networked systems within the domains of future air traffic management systems (Joint Planning and Development Office 2010), network-centric military operations (Nelson et al. 2004), emergency response (Manoj and Baker 2007), and the use and control of Unmanned Aerial Systems (UAS) (Brown and Garcia 2009; Saunders and Beard 2010; Ahmed et al. 2014; Nawrat. M 2014). These studies have shown that poor network reliability and variability in response time decreases human performance, compounding to larger system inefficiencies (Bayrak and Grabowski 2006); additionally, other research has studied the limitations of human attention and its effect on system performance. As the network complexity increases, which leads to more demands on the human operator, the whole system’s performance starts to degrade (Rosenfeld et al. 2008). Overall, these studies support the hypothesis that as a system or networked system increases in complexity or the load on the human operator, the overall efficiency and effective of the system decreases.

As the noted studies and others have identified, in order to gather requisite human–machine performance data, human-in-the-loop experiments built within complex simulations can be conducted to gather this data. However, due to the size and complexity of these networked systems, experimental data is insufficient to properly replicate the entire system. Therefore, other scientists have modeled many aspects of the network in order to isolate variables and to also test human automation performance metrics, task-specific network parameters and individual cognitive factors (de Visser et al. 2010; de Visser and Parasuraman 2011; Ahmed et al. 2014). Validated human performance models are utilized in these system experiments to replicate interactions and to determine their ability to predict system performance with multiple operators, especially as system complexity increases and its properties change over time. By reducing complexities in the system, they reduce the mental load for an operator which can improve their performance.

Of interest to this work, is research on the use and operator mental load when deploying multiple UAS's in different situations (Cooke 2006; Cummings et al. 2007). Other research has been conducted on managing the mission of surveillance, including search and rescue tasks (Parasuraman et al. 2005, 2009, 2011). Additionally, other probabilistic models predicting human-automation performance in networked UAS situation have been proposed. Fan et al. (2010) and Heger and Singh (2017) modeled the human operators dynamically with a Markov model in order to encapsulate the random transitions that effect decision-making and task performance. Another research group used discrete-event task simulations on operators to model the performance effects of different workloads and vehicle utilizations with UAS's (Donmez et al. 2010). These studies focused on the performance of the human operator as more UAS's were assigned to them and additional areas of search were added. As predicted, as the task load (TL) was increased, the performance decreased. Additional research was conducted to determine how performance was affected when imperfect information was given to the operator. Overall, the results indicated that as the information provided to the operator decreased in quality (either misinformation or communication interference) the performance was again degraded as extra mental capacities were diverted to decipher the messages (Wickens et al. 2006; Cummings and Guerlain 2007). Of importance to this work, is that these research areas provide a range of dynamic probabilistic human operator models which provide evidence which supports the hypothesis that they can generate sample-based performance prediction statistics via repeated random simulations of closed-loop task execution. As stated by Ahmed et al. (2014) they can also potentially provide useful insight into specific scenarios that lead to good/bad system performance.

There are other variables that can also be researched when looking at a human operator. As the previous research indicated that the TL increases with complexity of the system, individual operator's performance still varies based on how well they can handle this extra mental load. This variance is categorized as the working memory (WM) of an individual. In one experiment, this mental capability was estimated by focusing on how well the operator can maintain focus or their attention on assigned visual search tasks while coping with distractors (Engle 2002; Ranzini et al. 2017). Other research concluded that WM is a key component in executive control processes that is important to multi-tasking and making time-critical decisions (Endsley 1995; Parasuraman and Jiang 2012). Of the indicated research, most of it focuses on the TL and WM of operators and its effect on how well they can performance their tasks under different conditions.

Research important to this work was conducted by de Visser et al. (2010) and then re-examined by Ahmed et al. (2014). What both of these studies concluded was that TL and WM had an impact on performance, but they also added message quality (MQ) into the experiment and estimated its impact, in conjunction with WM and TL, on performance. MQ was the clarity of the information that was given to the operator through the networked system. Within the experiment, MQ was banded within three categories for quality: no message, noise message, clear or relevant message. This related to the messages that individuals (4 operators) send to other members of the team. Each member saw the same complex scenario on their screens with the goal of working as a team to share information. Concerning MQ, no message is self-explanatory – nothing was sent to the operator and they had to complete the task on their own from what they saw on their screen. Noise message was a message that could assist the operator, but only parts of the message were heard by the operator. Only random parts of the message were actually transmitted, with static filling the rest of the message. Clear or relevant messages were completely clear with no interference. The operator received the messages that other team mates send to the operator. They created a composite score consisting of several criteria including earning points on how well they played the experiment’s game and titled it Dynamic Distributed Decision (DDD) game score (see Figure 6). The

DDD was designed by the team as an air defense simulation task environment which provides a flexible framework to study individual and team decision making performance (de Visser et al. 2010).

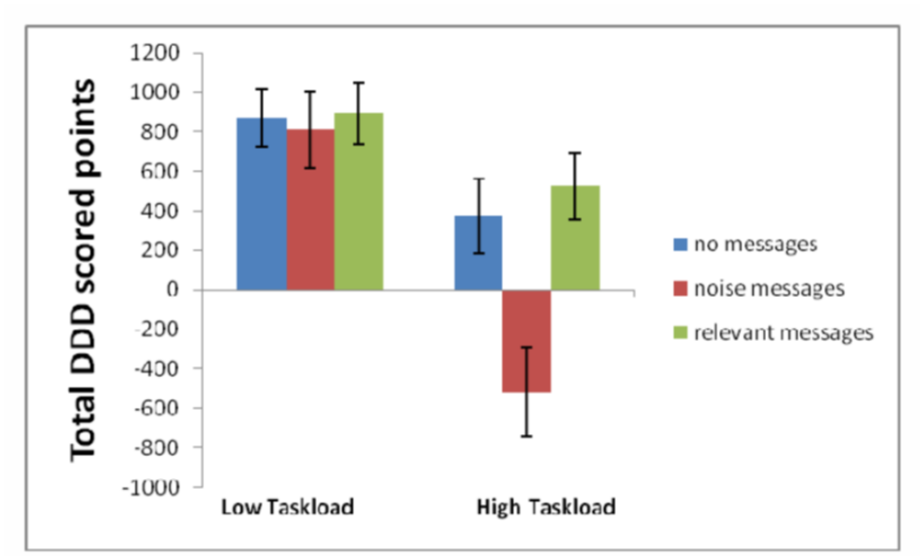


Figure 6 DDD Game Score Task Load x Message Quality condition Interaction. Source (de Visser et al. 2010)

The outcome of these experiments concluded that the TL of the operator increased as the MQ decreased and the performance of the operator decreased as the operator struggled to handle all tasks. Teams of operators focused on their individual performance with a “no message” MQ, but noise messages distracted the operators and resulted in significantly lower scores.

For this work, human cognition through team performance is represented through the metrics of TL, WM, and MQ.   Their interaction with this DSA model is replicated in Figure 7, focusing on the communications between the two analysts but also the cognitive levels within their own brains.

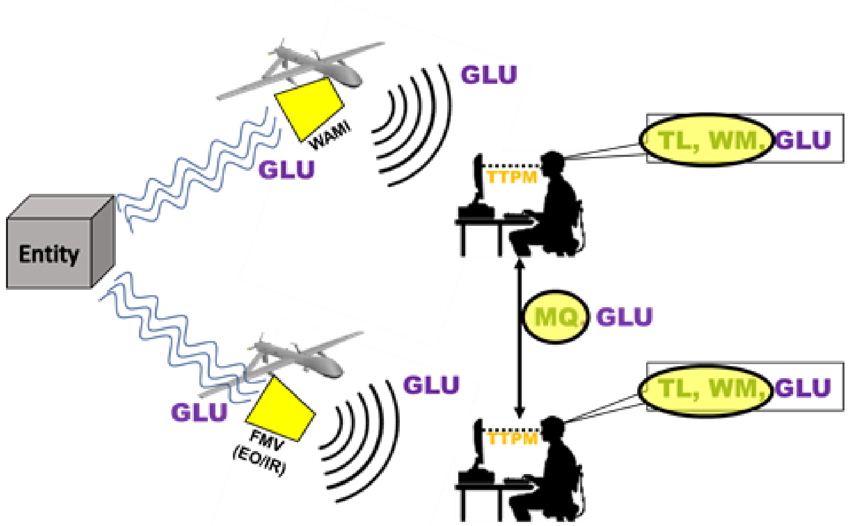


Figure 7 Human Cognition metrics utilized in this work.

2.6. Relationship with Training

Existing literature on communication indicates a strong correlation with training as a team and the quality of communications that occurs within or outside that team (Patrick et al. 2006; Cooke et al. 2013; Endsley 2015; Rybing et al. 2016; Sorensen and Stanton 2016). Additional research also indicates a strong correlation between training and SA concerning teams (Patrick et al. 2006; Walker et al. 2008; Patrick and Morgan 2010; Seppänen et al. 2013; Sorensen and Stanton 2013). Therefore, for this work, the assumption is that the team with the highest SA and cognitive communication performance scores is also the highest trained in the communication requirements for this experiment. This training, as supported by the research, should let the team perform better due to better communication and SA of the environment.

The level of training for a team can be measured in different ways, but the desired methods is to evaluate performance outcomes (Kraiger et al. 1993; Kirkpatrick 2006; Alvarez et al. 2010). For this work, the assumption is that the team with the highest cognitive performance metrics and SA has the highest level of training. As supported by the research, these teams should also perform the best. Another aspect of team performance is the assumption that that individual team members are proficient in their technical areas of expertise (Straus et al. 2019). In this case, these individuals are trained and proficient on the use of their computer systems and the communication protocols required for their job. This will also indicate a positive correlation between the proficiency level of the individual and team performance. The teams with individuals that are better trained, as demonstrated by higher proficiency, will perform better on accomplished certain tasks.

Another aspect of training is to prepare individuals and teams to perform under conditions of stress. Military teams, emergency medical personnel, and any task that must be performed under a time constraint creates stress. This includes information monitoring, communication to develop situational awareness, and shared mental models and training on these skills is critical for team adaption to stressful conditions (Entin and Serfaty 1999).

Sponsored by the Office of Naval Research, the Tactical Decision Making Under Stress (TADMUS) program, examined the nature of stress in tactical crews, the effects of stress on decision making, and strategies to mitigate stress including training and design of information displays (Cannon-Bowers and Salas 1999, 2009). Significant outcomes from this program identified two categories of operational stressors:

(1) Task-related stressors, which are inherent in the task, such as workload, time pressure, information uncertainty, and auditory overload.

(2) Ambient stressors, which are in the environment, such as auditory or visual distractions, performance pressure, and fatigue due to sustained operations (Cannon-Bowers and Salas 1999).

Of importance to this work, these stressors from both categories can be simulated. Teams can be trained and evaluated in simulators with the use of scenario-based training. Scenario-based training is when a team must perform certain tasks in a scenario designed to increase stress and replicate real-world conditions (Kirkpatrick 2006; Cannon-Bowers and Salas 2009; Salas et al. 2013; Nazir et al. 2015; Hixson et al. 2015; Straus et al. 2019). These research studies also provide evidence that the level of individual training impacts the performance of multiple team scenarios with respect to with respect to collective skills, which involve perceptual, decision making, communication, and coordination activities. However, more research is needed to understand the association between the type of scenario and training simulation that is ideal when compared to levels of expertise for individual training (Kraiger et al. 1993; Noble 2002; Alvarez et al. 2010; Straus et al. 2019).

2.7. Calculating Cognition

In order to be used by other researchers, Ahmed et al. (2014) provided three different models that could be utilized in other experiments. A linear model is provided that is helpful to system designers that are looking at a model to provide a basis for networked human-machine systems; however, this linear model is insufficient for extended performance predications that are not similar to the original experiment. For application that is dissimilar to the original experiment, the researchers present a probabilistic Gaussian process model and Bayesian network model to provide more robust, statistical predictions. Cross-validation of these models on predicting performance show that the following linear model adequately captured the performance measures from the Gaussian and Bayesian models.

For this work, the linear model is described below to better illustrate the variables and weights incorporated into the work.

Equation 1

$$\boldsymbol{Y = a + b_1 TL + b_2 MQ + b_3 WM + \varepsilon}$$

Within the linear model, Y is the performance measure of the cognitive ability of a team to compete a specified task. A constant bias term, *a*, on team performance is incorporated first into the model. TL, or Task Load, is multiplied against a regression weight, b_1, from the data collected from the original experiment. This is added to the product of MQ, or Message Quality, and another regression weight, b_2. The final cognitive metric WM, or Working Memory, is multiplied to another regression weight of b_3. To finish the model, a final value of the standard error of the estimate is added, estimated from the original experiment data via least squares. This formula is based on the original experiment which creates a distribution starting at a point greater than zero due to it being on the experiment's data.

However, the performance measure of Y cannot be easily integrated with the probabilistic outcome of Acquire-TTPM that is utilized by FOCUS and something that could be more easily coded into a program. In order to better integrate these two results, Ahmed et al. (2014) proposed a Bayesian Network conditional probability table (CPT) based on the results of their experiment that provide a probability performance metric expressed in Table 1.

Table 1 Bayesian Network CPT on the performance of an individual based on varying values of TL, MQ, WM. Source (Ahmed et al. 2014)

P(H=2 | TL, MQ, WM = hi)			
TL	MQ		
	all relevant	some noise	no messages
low	0.99	0.95	0.95
hi	0.92	0.81	0.68

In this table, H indicates high values for the three variables. For this experiment, the “hi” or high TL will be used with the additional high WM. The MQ will have three variables. From the original experiment, the values are 1 (all relevant), .2 (some noise), and 0 (no message) and this will also be utilized in this work. Due to time constraints and other stressors, the simulated human operators will be evaluated using a high TL that is degrading their performance. The “no message” column indicates a very noisy message which further degrades the performance of the team. These values will be utilized to alter the communication variables within FOCUS.

2.8. Targeting Task Performance Metric (TTPM)

The human cognitive metrics and situational awareness previously discussed are related to the communication ability between each human analyst and their ability to handle what is going on around them. This section explains the ability of each human analyst to actually perform their specified task of detecting or identifying a specific entity on a computer monitor, as shown in Figure 8. Research on this subject is well documented with TTPM (Hixson et al. 2017) and is one of the reasons it was chosen. However, the main reason is its utilization as the foundational component of the simulation, FOCUS, employed for the experiments covered in the body of work.

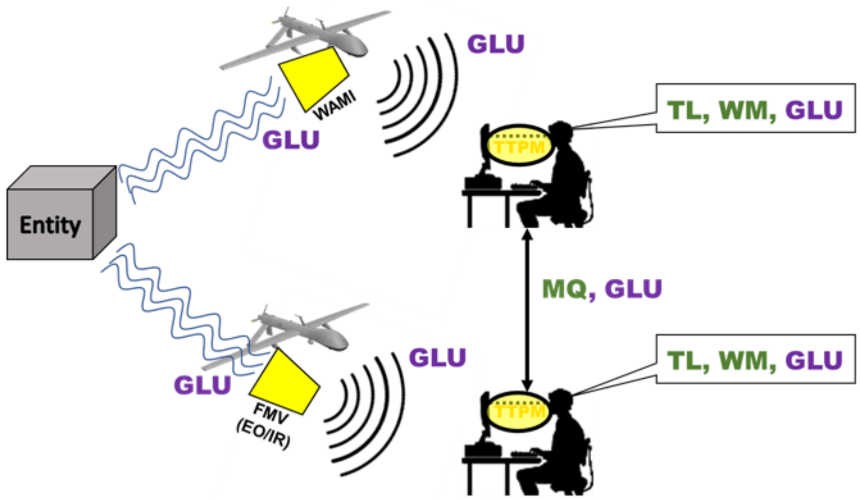


Figure 8 TTPM utilized in this work

The TTPM is a sensor performance model designed to predict task performance of identifying a specific entity or target in this case, and its performance has been validated by research establishing probabilities based on multiple conditions and ranges (Hixson et al. 2004; Vollmerhausen 2004; Vollmerhausen and Robinson 2007; Vollmerhausen et al. 2008a, b; Preece et al. 2014). It is the basis of the U.S. Army's electro-optical target acquisition model that is used to predict how well a human observer can detect and identify an entity or target (Vollmerhausen 2009).

The TTPM incorporates the limitations of the human visual system (HVS) using the research based upon the contrast threshold function (CTF). Developed by Beaton and Farley (1991) and also utilizing the work from Barten (1990), the CTF is a function based upon the dependence of an average luminance, the number of eyes, and the apparent target angle. Their research developed the CTF into a numerical representation of the ability of the HVS to detect the presence of a low-contrast sine wave as a function of spatial frequency. In experiments, an observer was presented a sine-wave pattern on a screen and a response is solicited as to whether they can detect the sine wave, as shown in Figure 9.

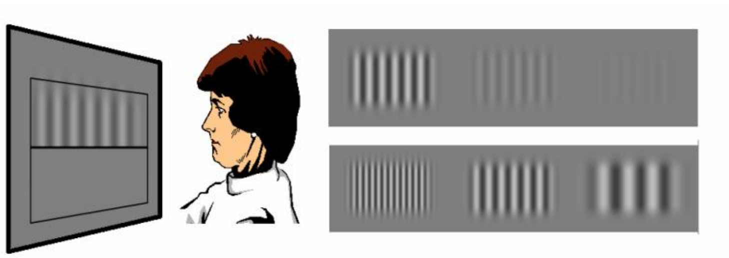


Figure 9 Experimental setup for measuring CTF. Top right shows variation in contrast. Bottom right shows variation in spatial frequency. Source (Vollmerhausen 2009).

The goal was to measure the amplitude of the sine wave that is just visible to the observer. Procedurally, the experiment set a constant luminance while the contrast of the screen was reduced until the observer specified they could no longer see it. As an example, this decrease in contrast from left to right is shown at the top right of the figure. Conclusions from the experiment indicated that the operator's success in identification was depend upon several conditions of the image stimulus, including orientation, luminance levels, stimulus size, surround luminance, and viewing distance (Barten 1989, 1990).

In an equation, TTPM is composed of several required dependent variables and their corresponding functions. The system CTF (CTF_{sys}) is composed of the naked eye CTF (CTF_{eye}) degraded by blur and noise from the visual sensor and shown in the imager. As shown in Equation 2, TTPM is a function of the area between the target contrast and the systems CTF (Hixson and Teaney 2016).

Equation 2

$$\boldsymbol{CTF_{sys}(\xi) = \frac{CTF_{eye}(\xi)}{MTF(\xi)}\left(1 + \frac{\alpha(L)^2 N(\xi)^2}{L^2}\right)^{1/2}}$$

The system CTF is a product of the CTF of the naked eye, CTF_{eye}, at a specific spatial frequency, $\boldsymbol{\xi}$, and the system modulation transfer function, MTF (ξ), at a specific frequency in $(\text{milliradian})^{-1}$. This product is then multiplied to the outcome of the function based on the display luminance of the computer monitor, L (>0), the noise filtered by the display and visual system, N (ξ), and the calibration constant dependent on the luminance displayed to the eye, α. An example of the produced CTF curve is shown in Figure 10. Hixson, et. al. (2017) use this figure to show that TTPM represents the limited amount of visual information observable to human operators that allow them to detect a specific target.

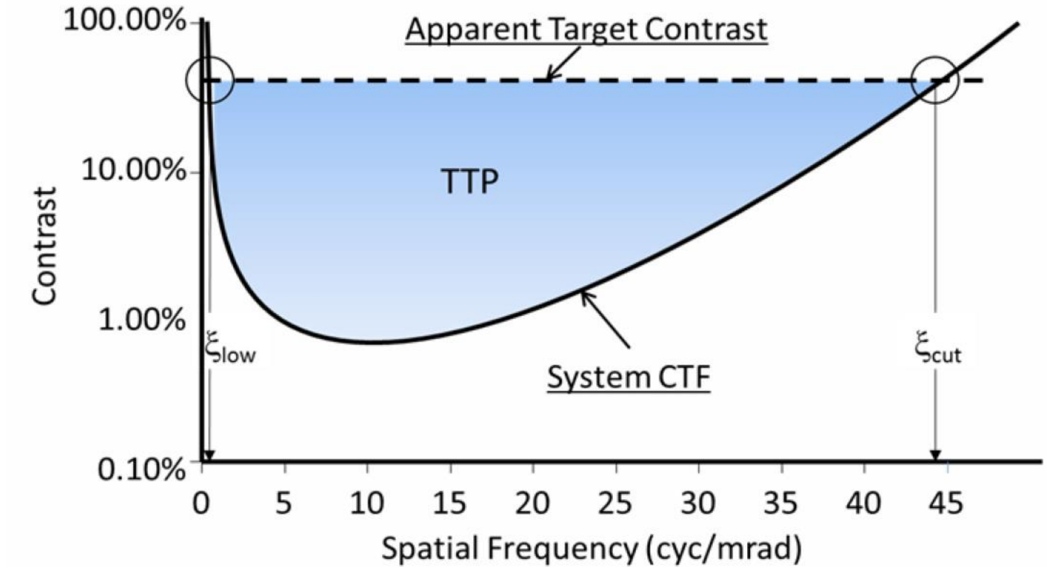


Figure 10 Example of CTF Curve. Source (Hixson et al. 2017)

The actual TTP metric (TTPM) is shown in equation 3, where C_{tgt} is the target contrast based on research on specific vehicles and ξ is spatial frequency (Hixson and Teaney 2016).

Equation 3

$$\boldsymbol{TTP = \int_{\xi_{low}}^{\xi_{cut}} \sqrt{\frac{C_{tgt}}{CTF_{sys}(\xi)}}\, d\xi}$$

The limits on the integral start (low) and end (cut) are where the target contrast intersects the CTF_{sys} as shown in Figure 10. As part of the operation, the integration is conducted two times, once with the horizontal CTF and then with the vertical CTF. The geometric mean is then calculated from these results. These results then feed the Equation 4 (Hixson et al. 2017).

Equation 4

$$\boldsymbol{V = TTP\left(\frac{CD}{R}\right)}$$

This equation determines the number of times it takes an operator to search a screen, or resolvable cycles - represented by V, to detect the entity or target. This is based off the TTP value from equation 7, multiplied to the produce of the target's characteristic dimensions in meters, CD, divided by the distance between the target and sensor in kilometers, R.

The final step is to take the resolvable cycles on target, V, and relate it to the task difficult factor (V50). V50 is the resolvable cycles necessary to successfully perform a target acquisition 50% of the time. Therefore, V# (e.g. V50) will always be less than V but will always be above zero. P_{∞} is the probability of task completion given infinite time to complete it. This relationship is depicted in Equation 5 (Hixson et al. 2017).

Equation 5

$$\boldsymbol{P_{\infty}} = \frac{\left(\boldsymbol{V}/_{\boldsymbol{V50}}\right)^{\mathbf{1.5}}}{\mathbf{1} + \left(\boldsymbol{V}/_{\boldsymbol{V50}}\right)^{\mathbf{1.5}}}$$

Graphing this relationship is shown in Figure 11.

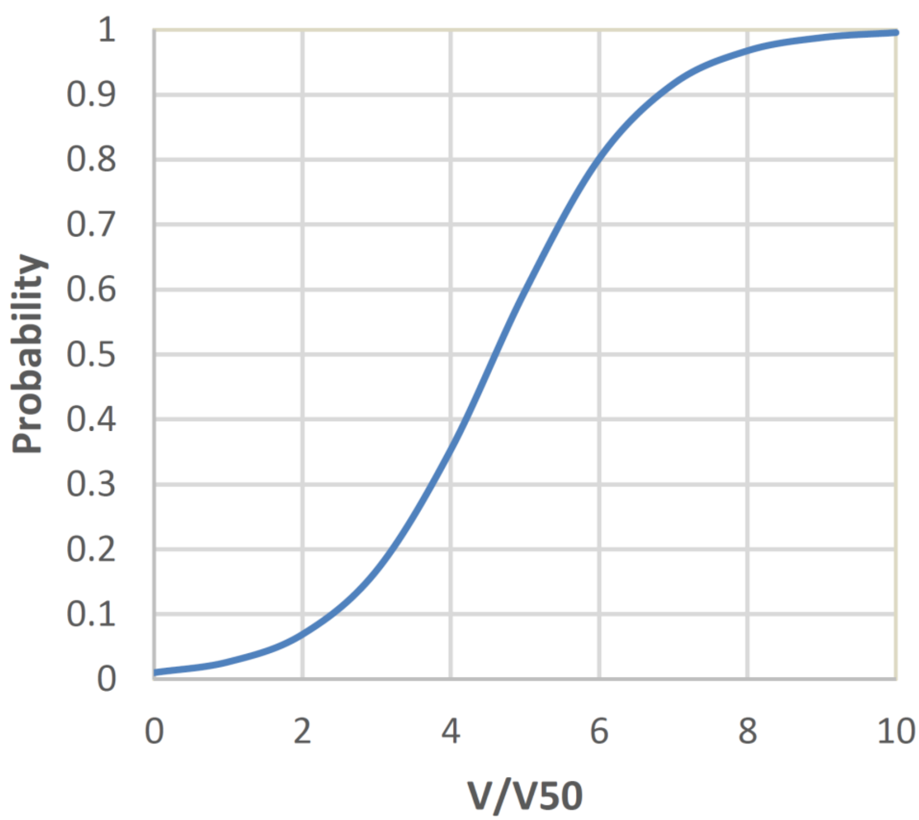


Figure 11 Probability curve of Equation 9. Source (Hixson et al. 2017)

Through laboratory observer perception testing, the task difficulty factors are measured empirically for each waveband and task acquisition task (e.g. detection and identification) (Driggers 2001; Driggers et al. 2006). Repeating this process for different ranges builds a range performance curve as shown in Figure 12.

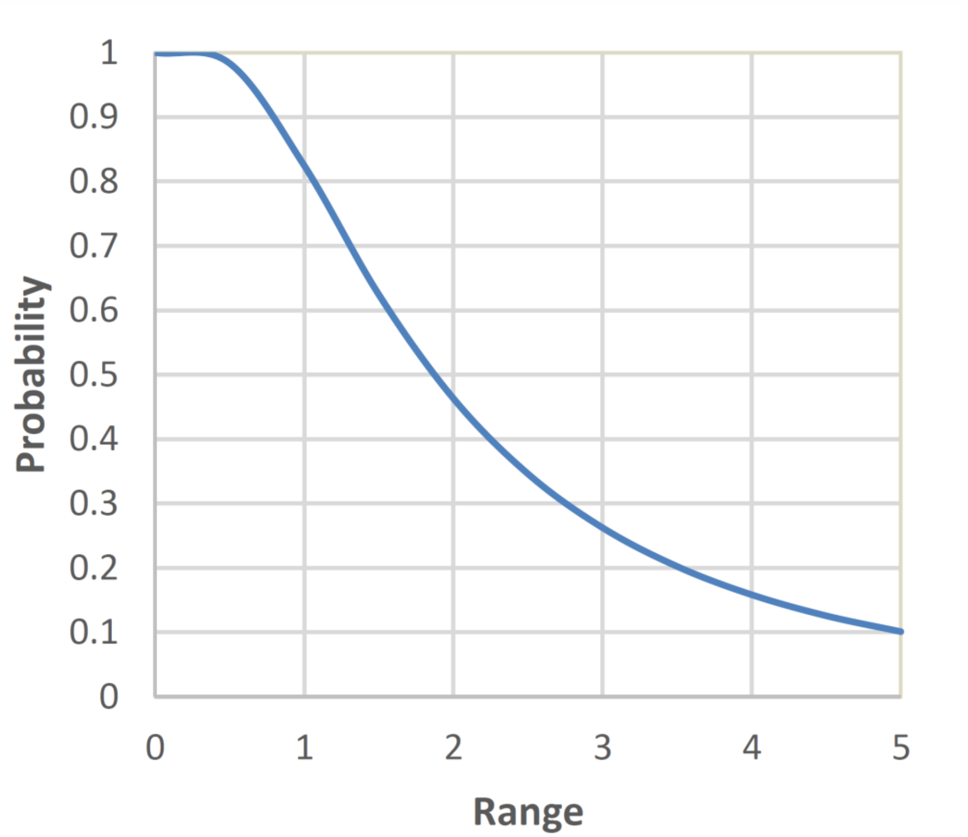


Figure 12 Probability curve based on probability to complete the task range in kilometers. Source (Hixson et al. 2017)

Within the electro-optical (EO) / infrared (IR) sensor category, the TTPM covers their performances equally. Both of these electro-optical sensors are used in this work. EO imagers reflect light (sunlight or starlight) and usually detect energy within between 0.4 and 2 microns on the spectral band. IR (or thermal) imagers detect emitted electromagnetic energy (heat) from objects and operate with the mid-wave infrared (3 to 5 microns) or the long-wave infrared (8 to 12 microns). Even though signal and noise units for describing thermal imagers are different those modeling reflected light, the basic target acquisition theory used to create TTPM is exactly the same. (Vollmerhausen and Jacobs 2004). Each has an operator or analyst looking at a visual display of a target and TTPM predicts the effects of blur, noise, and display characteristics on target acquisition task performance.

2.9. Geographical Location Uncertainty

Tied to the concept of “ground truth” within situational awareness, there is not only a struggle to have a common understanding of a situation but where an entity is actually geographically located. There is uncertainty in the actual geographical location of the entity (at a specific point in time) and what the human operator estimates and how the sensors actually sense the entity and calibrate its location. This error stems from the mis-calibration of the optical sensors, laser distance sensors, GPS navigational estimates, and many other areas. It is a result from the reductionism of taking the infinitely complex geographical world and creating an abstraction of the real world through digital or data modeling methodologies (Heuvelink 1998; Zhang 2002; Jackson et al. 2013; Mullen et al. 2015). Geographical location error, consisting of geodata uncertainty or geospatial data uncertainty, has been a Geographical Information Science research topic for many years (Zhang 2002; Shi 2010; Caers 2012; Mullen et al. 2015; Jackson et al. 2013). For this work, geographical location uncertainty will be used as an all-encompassing title that incorporates concepts like ambiguity, inaccuracy, imprecision, error (unknown or not quantified error), and subjectivity as it relates to geographical location. All the parts of the distributed system that is calculated to have GLU in this work is depicted in Figure 13.

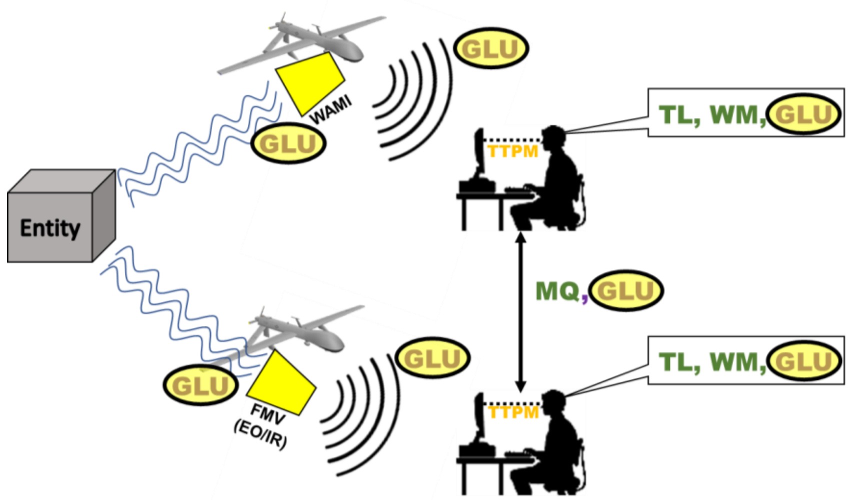


Figure 13 Distribution of GLU within this work's framework

Since uncertainty in geographical location is a challenging concept, research has been conducted on visualizing uncertainty solutions (Brodlie et al. 2012; Mahabir, Ron et al. 2018). However, research on how uncertainty effects reasoning and decision-making continues to look at different aspects of this complex challenge (Johnson and Sanderson 2003; MacEachren et al. 2005). Of importance to this work, is the research that has been conducted on the performance of a team that communicates uncertainty through written forms (emails) and how it doesn't match the performance of other teams that use maps or other graphical means (Kobus et al. 2001; Shattuck et al. 2009). Other work has been done that studies the effect of uncertainty on positional accuracy. All of which note that uncertainty, in whatever form they studied, impacts the ability of a human being to estimate the exact location of an entity(Jackson et al. 2013; Mullen et al. 2015). Brolese et al. (2006) evaluated improving a human's ability to estimate location and how uncertain surroundings impact their ability accurately communicate this position. Hope et al. (2007) researched the negative impact of uncertain locations spatial decision making. This research was also reference in Kirschenbaum's et. al. (2014) evaluation of several other studies that studied how positional uncertainty impacts the performance of teams and individuals. Such research indicates that the uncertainty in estimating an entity's position impacts the performance of teams and decreases the effectiveness of decision making.

Finger's et. al. (2002) study used game theory (and game tasks) in a dynamic environment and the added constrain of time. In this game, subjects tried to identify an unidentified moving object that moved across a computer monitor. Competing against other participants, subjects tried to have the highest number of guesses in the least amount of time. Similar constructs were conducted in several others studies that included this dynamic environment and measured performance of a particular task (Bisantz et al. 2005, 2011; Hope and Hunter 2007; Riveiro et al. 2014). Overall, these studies indicate that uncertainty increases the mental work load on the participants and takes longer to complete a task.

Another aspect relevant to this work is the measurement of a participant's performance and how this impacts the completion of a task involving uncertainty. Cognitive research on expertise indicates that this level of skill impacts how decisions are made, especially when uncertain aspects are involved (Klein 1998; Patrick et al. 2006; Walker et al. 2008; Patrick and Morgan 2010; Seppänen et al. 2013; Sorensen and Stanton 2013, 2016). Several of these studies involve groups of subjects with varying levels of expertise or experience. Roth (2009) supports this assessment and his results indicate that expertise has a significant effect on task performance. Hope's et al. (2007) work also showed a high degree of correlation between expertise and high performance on specific tasks relating position accuracy and uncertainty.

Ideally, to reduce uncertainty, the first step would be to identifying the sources of error; however, accounting for all sources is usually a futile endeavor. One method to account for all of the imprecisions is to model the uncertainty (Heuvelink 1998). In this scenario, the inaccuracies within the system have propagated to the first observer – the one trying to detect the entity or target. With the inclusion of their final errors, a level of uncertainty in location is communicated to the second observers – the one trying to identify the entity. This uncertainty is usually indicated through errors in positional accuracy or a point in space.

2.10. Optical Sensors

Two separate optical sensors will be used in this work. This section will provide information on these two electronic optical and InfraRed (EO/IR) sensors: Full Motion Video (FMV) and Wide Area Motion Imagery (WAMI) sensors. These sensors are depicted in Figure 14.

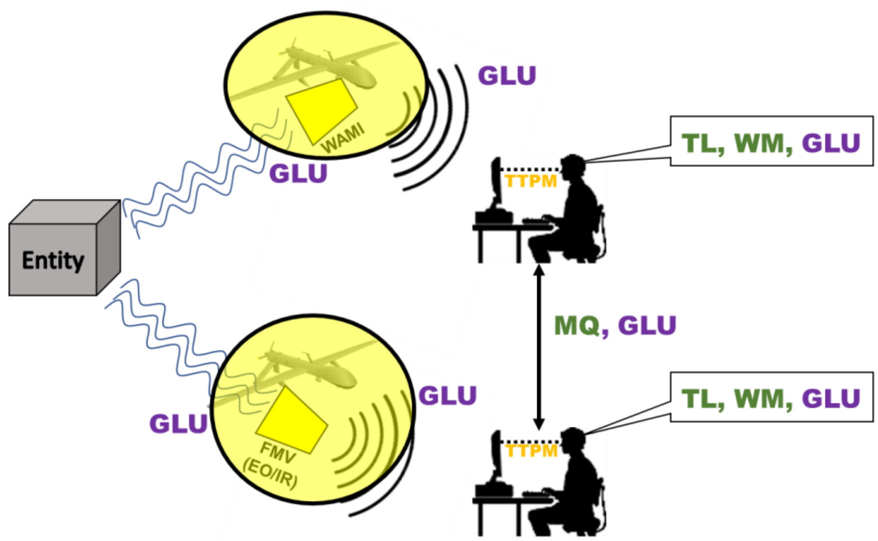


Figure 14 Sensors utilized in this work

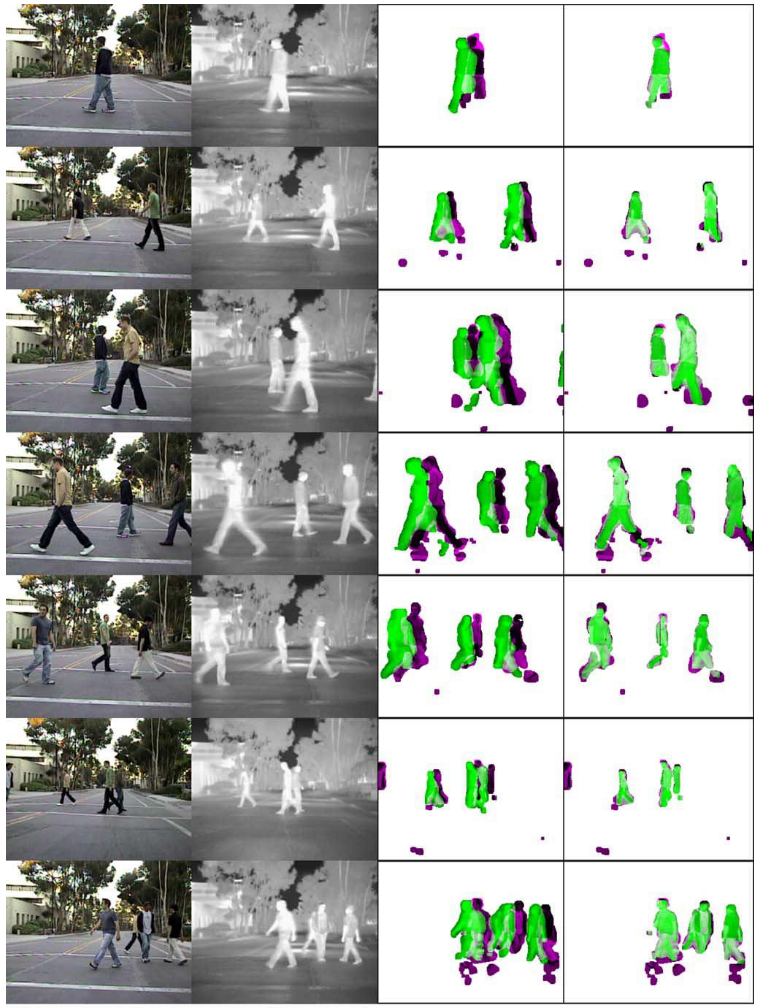
2.10.1. Electronic Optical and InfraRed (EO/IR) and Full Motion Video (FMV)

Technology and environmental challenges have created obstacles to detecting and identifying entities through EO/IR images in the past. Images captured by surveillance cameras, aerial vehicles, and other stationary and non-stationary sensors are generally characterized by limited resolution, poor contrast and low signal-to-noise ratio (Alam and Bhuiyan 2014). However, advances over the past decade have created solutions to these problems through new software, hardware, and wireless transmission enhancements. It is common place to find surveillance cameras that are high definition resolution and provide exceptional recorded clarity of an image for an area. For this work, high definition is defined as least 1080 pixels (1080p) that comprise a video image. The more pixels the higher the resolution (pixels per image) (Sanna and Lamberti 2014).

Earlier research on EO/IR focused mainly on the visible light spectrum with a focus on both single and multiple monocular or stereo cameras to develop solutions to finding and tracking targets. However, the main concern with visible light sensors, and of particular concern with those agencies and departments that must find an entity in all weather and light conditions, was its unsatisfactory performance under poor visibility conditions (Ricaurte et al. 2014). Later research in the 2000's continued with the visible spectrum but also started to incorporate more research with the infrared spectrum that could pierce poor weather and see in all light conditions (Fernández-Caballero et al. 2014). Since detecting entities in poor visibility was a priority in many research objectives, experiments focused on the long-wave infrared (LWIR) spectrum (in the range 8-12 nm) due to its ability to sense heat sources at night or through smoke, fog, and other atmospheric conditions. Of specific interest in the study of IR is forward-looking infrared (FLIR) technology because in this sensor the intensity of an object mainly depends on its temperature and radiated heat and is not influenced by light conditions and object surface features (Sanna and Lamberti 2014).

FMV sensors in this work are high definition cameras mounted in a mobile gimbal (protective mobile cover attached to an aerial platform) that provides almost 360 degree of movement laterally and 90 degrees of movement horizontally (Groenert and Bryski 2009). Due to the high resolution of the pictures captured by these sensors, they have demonstrated the ability to detect a man-sized entity at 40 kilometers or a large vehicle at 80 kilometers by their optical and electronic zoom capabilities (Eismann et al. 2010). The sensor utilized in this work is a variation of the WESCAM MX-20 (2019a) which has both infrared and electro-optical (visible light) capabilities. PS2 Surveillance Services is an example of a company that provides surveillance services and utilizes sensors similar to those in this work (2018b). For this work, these FMV sensors will be utilized to identify a specific entity. Through their use of visible and infrared capabilities, it has the capacity to identify a specific target.

In detecting, identifying, and tracking objects with EO or FLIR, scholars have used learning based (Chan et al. 1996; Lin-Cheng Wang et al. 1997) and model-based methods (Lamdan and Wolfson 1988; Olson and Huttenlocher 1997; Venkataraman et al. 2011; Gong et al. 2014a). Other than algorithms, multi-sensor phenomenologies have been attempted to improve results of detection. In this work, the term, “multi-sensor” is defined as more than one sensor is looking at the same target and consists of several categories: multilook, where one sensor gets several looks at the target from different aspects; and multimode fusion, where sensors of different modalities sense the target (e.g., acoustic and EO signals are fused) (Bhanu 1993). An example of this multi-sensor effort is the merging of images of the IR spectrum and the visible spectrum in detecting and tracking entities as depicted in Figure 15. Krotosky and Trivedi (2007) used a cross-spectral stereo-registration methodology to better detect pedestrians for automated cars. They use both visible and infrared to detect the people in the street.



(a) (b) (c) (d)

Figure 15 Cross-spectral stereo-registration results for pedestrian detection. (a) Color. (b) Infrared. (c) Unaligned. (d) Aligned. Source (Krotosky and Trivedi 2007)

2.10.2. Wide Area Motion Imagery (WAMI)

WAMI sensors are designed to detect multiple entities over a large geographical area. Enabling the ability to actually monitor these larger areas has been the technological evolution of digital image processing systems that combine video imagery from multiple sources. As seen in Figure 16, a vast majority of WAMI systems consist of multiple cameras whose FOVs overlap one another and usually cover 360 degrees from their platform. These images are then digitally merged together to create on image which special software (or viewer) can then interpret the image (or video) for an analyst (Priddy and Uppenkamp 2012).

Figure 16 WAMI Summary: Sensors, Image Exploitation, and Viewer. Source (Priddy and Uppenkamp 2012)

With such a wide FOV, research has focused on security (e.g. perimeter surveillance) (Porter et al. 2010; Blasch et al. 2014), environmental analysis (e.g., monitoring flood damage) (Asari 2014), and emergency response (e.g., disaster relief)(Gao et al. 2013; Young and Foulkes 2015), and the results of this research have been the development of numerous methods and techniques used in processing WAMI data . As shown in Figure 17, merging several optical sensors, larger areas of higher resolution imagery can be better analyzed due to the ability to zoom in on areas of interest (AOI).

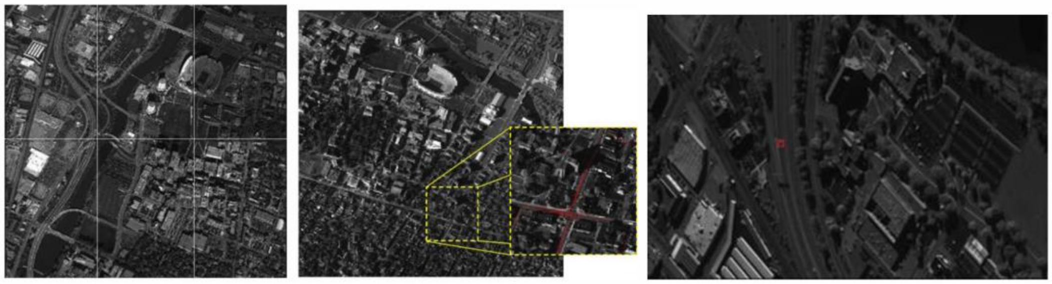


Figure 17 WAMI Data from the Columbus Large Imagery Format (CLIF) collection. Source (Mendoza-Schrock et al. 2009)

Due to the multiple, higher resolution optical sensors, the size of one frame or image from WAMI sensors can consist of multiple gigabytes of data. These sensors have the capability to image small city-sized areas at approximately 0.5m a pixel and about 1 or 2 frames per second (Porter et al. 2009). The large data file sizes and high-resolution images (compared to higher fidelity EO/IR sensors with narrower FOVs) create image files that require a data flow of over 100Mb of data per second, or over 400Gb per hour (Wu et al. 2015a). However, WAMI sensors are typically used when organizations need constant coverage of an area (a.k.a. persistent surveillance), 3D processing for terrain analysis (due to different perspectives of the sensors), and target tracking (Porter et al. 2010). Research has also focused on some of the key challenges for digitally processing WAMI sensors, which include low frame rates, extended camera coverage, multiple targets, weak target texture, and environment occlusions.

2.10.3. Describing a Wide Area

Research organizes a wide area into three areas of interest, and these are represented in the columns within Figure 18. Within each column are several rows of themes that current research has studied. The first row, physical sensor models aid in registration, that when aligned support 3D terrain analysis. The second-row states that optics with geometry support segmentation for vehicle detection that support event processing over a spatial and temporal correlation. Finally, the third row reads as tracking is based on measurements from detections, it is the computational challenges that lead to activity-based intelligence (Blasch et al. 2012).

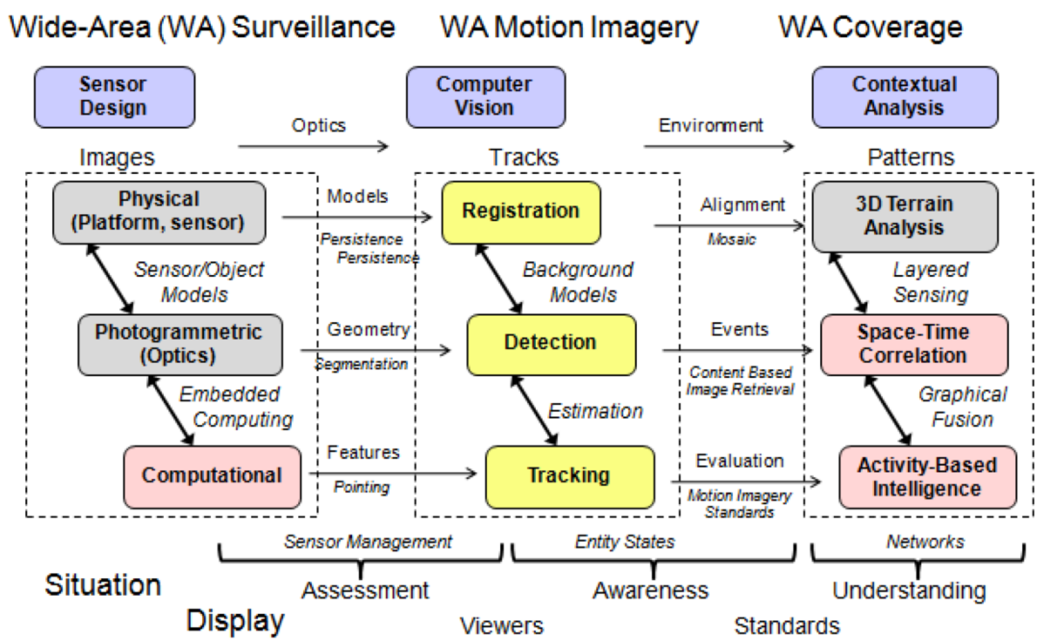


Figure 18 WAMI Processing Techniques. The colors denote areas of development with the Gray boxes as physical designs, yellow boxes are software exploitation, and pink is hardware techniques. Source (Blasch et al. 2014).

In order to maintain a continuous (or persistence) detection of an area, WAMI developments relied upon specific sensor and platform designs to sustain this capability (Rovito et al. 2008). These designs also improved sensor resolution to enable the detection and tracking of these targets that is critical for surveillance (Abidi et al. 2008).

Differing from surveillance, WAMI requires additional analysis to be conducted on very large image sizes. Due to the challenges of processing these big image files, different methods were developed that reduced the frame rate in order to accommodate for the low update rate due to slow download speeds of the radio communications (Porter et al. 2009).

Unfortunately, low-frame rates create problems in registering the images (Blasch 2009), from which techniques were created that layered different data (Mendoza-Schrock et al. 2009). Other techniques enabled for limited activity analysis due to the different layers, (Porter et al. 2009), interactive search (Porter et al. 2010), and track initiation (Cuntoor et al. 2010), even when constrained by a low-frame rate.

2.11. Airborne Surveillance for Vehicle Detection

Over the past two decades, video surveillance research and operational use of these systems has shown a favorable ability in detecting vehicles. Most of this research was done on fixed camera system, like traffic cameras; however, airborne video systems have attracted the most attention in recent research. Such platforms are particularly attractive due to their ability to move quickly, deploy faster, and have a larger FOV at higher altitudes. However, the technical drawback from this mobility is the ability of airborne video surveillance to visually track vehicles. As a fundamental task in visualization and pattern recognition, detecting the same vehicle from frame to frame is possibly the most difficult task. Several works that cover this field have created methods to localize, and narrow the search, concerning these moving vehicles (Veeraraghavan et al. 2003; Yilmaz et al. 2006; Ali et al. 2007).

The basic framework of airborne video is: (1) moving vehicle detection; (2) vehicle tracking; (3) behavior understanding (Hu et al. 2004; Meng Liu et al. 2008) . There are different methods to detecting moving vehicles: optical flow (Barron et al. 1992; Mak 2008), background subtraction (Yilmaz et al. 2006), temporal differencing methods (Lipton et al. 1998; Wu et al. 2015a) and pattern classifiers (Lin et al. 2009). For vehicle tracking, it is broken up into mainly four categories of evaluation (Hu et al. 2004; Yilmaz et al. 2006) region-based tracking, contour-based tracking, feature based tracking and model-based tracking. However, there is no clear-cut delineation between these categories, since algorithms or methods are sometimes integrated together. Additional complexity is added to these categories when tracking vehicles from an airborne platform. Airborne tracking is more difficult than from a stationary camera for four main reasons: (1) the motion of the platform is constantly changing; (2) the FOV of the video camera is limited; (3) changes to objects appearance or shape is dynamic during tracking due to illumination and angle of visualization variations; (4) background objects like buildings or trees obscure or block the target from the sensor resulting in loss of observation (Cao et al. 2012).

2.12. Aided/ Target Recognition (AiTR)

Aided/automatic target recognition (AiTR) is the term used to describe the research, projects, and processes covering automated or aided processing functions on imaging sensor data that enable the performance of operations ranging from simple cuing of a human observer onto a target to the complex, fully autonomous object acquisition and identification of these targets (Ratches et al. 2001). Automatic targeting recognition (ATR) describes the fully autonomous side of this research. An example of ATR is the terminal acquisition phase of a missile seeker as it guides itself onto a target. Aided target recognition (AiTR) focuses on the processes required to present image annotations to the human observer. Researches in this part of the field examine the human analyst's ability to make decisions on the veracity and complexity of generated information and the action taken(Plantz et al. 2008; Ratches 2011; Goley and Nolan 2012; Pei and Mutka 2013). Then they investigate how to improve these results through technology and other processes (Ratches 2011). In this work, only the AiTR side of the field will be addressed as the analyst's work cycle and the proper placement of technology in this cycle are examined.

A high-level simplified diagram of a generic AiTR algorithm is shown in Figure 19. First, an image from a sensor is inputted into the front end of the processor, after which, preprocessing conditioning is executed. Several actions can occur within preprocessing to include mostly standard image-processing techniques like noise reduction or removal, image orientation, etc. After these operations are conducted, features are then extracted so candidate regions of areas of interest can be segmented, anomalies identified, and detections declared. Once completed, higher levels of classification or determination can be processed. The last stage of this algorithm can be better explained by the example of two different military vehicles: classification (tracked versus wheeled), recognition (truck versus tank), and identification (M1 tank versus T72 tank) as depicted in Figure 19.

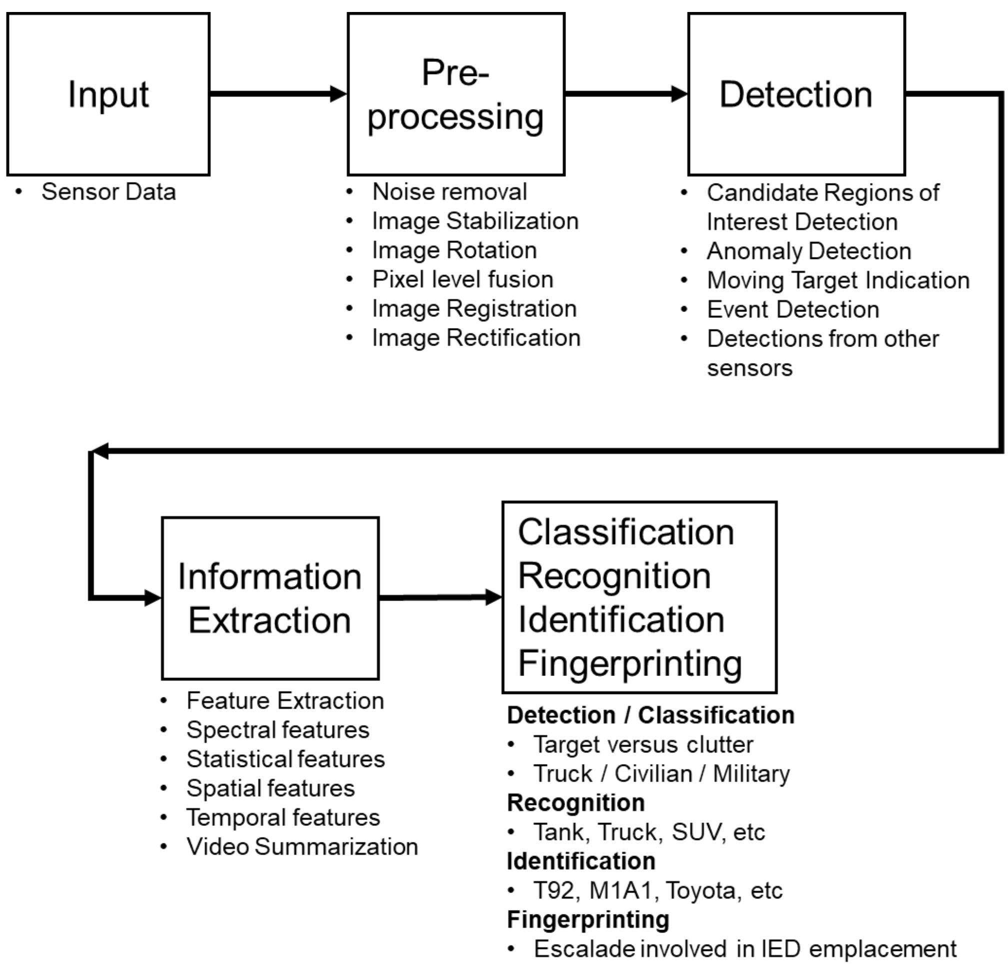


Figure 19 Generic AiTR algorithm showing discrimination functions processed on image. Source (Ratches 2011).

The role of AiTR is to assist the human observer in completing their assigned task. This assistance can be in detecting pedestrians on a busy street, determining if an entity is a car or other object, or some other aspect that requires automation to quickly analyze different electromagnetic spectrum results and match the results to a database(Snorrason et al. 1995; Lin-Cheng Wang et al. 1997; Olson and Huttenlocher 1997; Singh and Abdallah 2000; Mahalanobis and Muise 2001; Priddy and Uppenkamp 2012; Blasch et al. 2013; Li et al. 2014). Overall, it lets a human execute their assignment faster and with more precision.

In this work, the AiTR that will be utilized is designed to reduce the miscommunication and GLU between the detecting and identifying platforms. With the DSA theory, this would be an automated entity with its own SA that connects the platform and sensors of both types and also the human operators. As shown in Figure 20, the AiTR technology is the conduit between the sensors, platforms communication arrays, and the computers the human operators are utilizing. In this work, the first stage (1 in the figure) is that the WAMI sensor collects a visual image that is then processed by the AiTR. This process detects potential targets which are then transmitted to the WAMI operator (stage 2) who finds potential targets that match the entity description. This potential target is then sent back to the AiTR processor and forwarded to the FMV sensor on the other platform with a geographical location (with GLU incorporated), this is stage

3. The FMV sensor then rotates and zooms in on the location provided by the WAMI sensor and operator – the potential target. This image is then transmitted to the FMV operator for detection, analysis, and identification – stage 4. If the target is the specified entity, then the operator continues to track the target (Snorrason et al. 1995; Zhou et al. 2004; Blasch et al. 2013; Eismann et al. 2010).

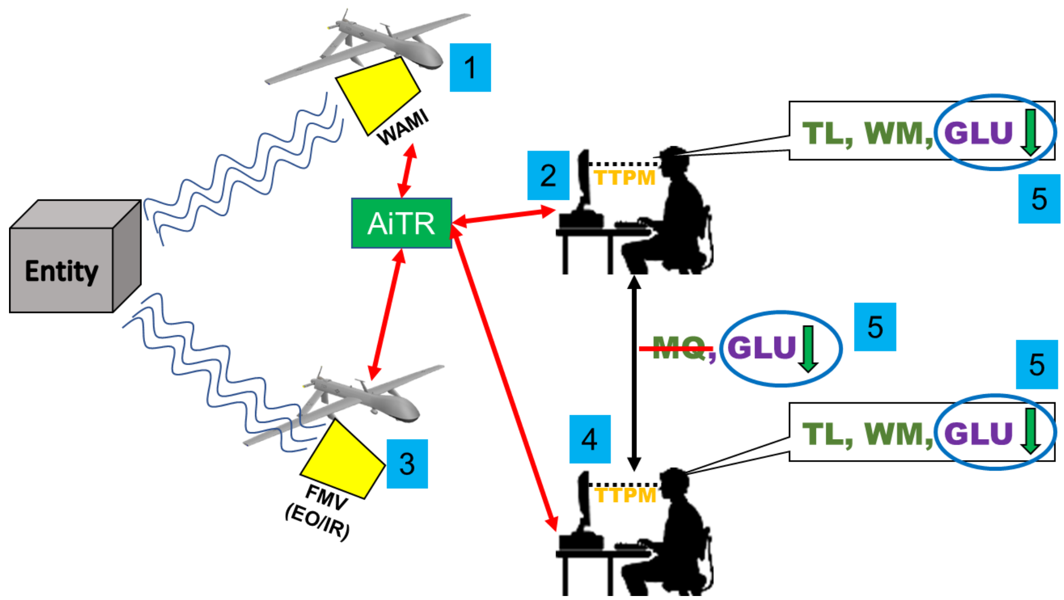


Figure 20 Layout of how AiTR will affect the operator's ability to detect and identify the targeted entity

AiTR impacts the experiment since the technology removes the need for verbal communication between the operators (removing the verbal MQ value) – as indicated in the stage 5 indicators in figure 20. Additionally, the GLU within the system is reduced since the human operators own estimation of the targets location will be removed. Within the research of visual analytics, AiTR provides an integral approach to improving decision-making by combining visualization, human factors, and data analysis through computer technology (Keim, et al. 2008). It meets the challenge to identify the best automated processes for the analysis task at hand – identification of a targeted entity. It has the potential to enhance the performance of a human operator by expanding the limits of the human brain as researched by Misra and Stokols (2012) with automation. Finally, AiTR is a method and model that can turn vast amounts of information into reliable, provable, and actionable knowledge (Kerren et al. 2013). Combining and integrating the strengths of computers and humans, the focus of visual analytics, and specifically this work, is to determine an optimal interactive process designed to extract useful knowledge from data. In this work, this is presenting the data from the sensor in a format that a human operator can quickly and accurately separate a specific entity from background clutter of an image (Keim et al. 2008). AiTR is potentially the technology that can assist in this process.

2.13. Summary of Literature Review

This chapter provided research on the critical topics for this work and its experiments. At its foundation is a review of visual analytics and its importance to merging the studies of human visualization and machine computing (section 2.1). This was followed by an overview of the steps necessary to finding and identifying an entity was explored followed by studies on situational awareness and an individual's awareness of their surroundings or location (section 2.3). Moving into the cognitive aspects of human being, research was presented concerning the overall model for this work concerning Distributed Situational Awareness (DSA) and how humans and non-humans and technological assets interact within a system (section 2.4). Of importance in this research is that each node in the system has its own situational awareness which is then communicated to other nodes. Human cognition in the context of team performance was defined and tied to how teams are affected cognitive performance metrics of TL, WM, and MQ when completing specified tasks (sections 2.5 through 2.7). This is tied to an individual's ability to detect and identify an entity which is measured by the TTPM (section 2.8). GLU was also defined and its research on uncertainty in location, which can also be propagated through a system (as supported by the DSA) (section 2.9). Finally, the optical sensors – both FMV and WAMI was defined and tied to surveillance concepts (section 2.10) and the importance of AiTR to this work (section 2.12).

3. RESEARCH QUESTION

3.1. Overview

This work aims to make a contribution by providing a team-based detection and identification performance model incorporating the theory of DSA and its effect on completing a specific task. The task being the ability to detect and identify a specific entity (yellow taxicab) within a complex urban environment. Conditions to accomplish task is the utilization of two unmanned aerial vehicles mounted with either a full motion video senor or a wide area motion imaging sensor and two human analysts creating a team to execute this task.

Basing this worked on the DSA theory, in which situational awareness is shared and communicated throughout the system, a team's cognitive performance capabilities (communications and detection/identification abilities) combined with the GLU from each node (human and non-human) is propagated through the system. With the cumulative results effecting the overall performance of the team in executing its task. From the aerial platforms with their sensors to the human operators analyzing the video images on their computer screens, each agent contributes to the uncertainty or situational awareness of the whole and effects each node of the system.

3.2. Research Questions

Given a team-based detection and identification performance model, which utilizes multiple sensors and incorporates the theory of DSA, how does message quality and GLU impact the team's ability to execute a specific task? Additionally, how does technology (AiTR) impact this task? That task being how long, in seconds, a yellow taxicab can be identified within a complex, urban environment. Situational awareness, for this body of work, comprises the integration of unique aspects geographical location uncertainty, human communication performance, human visual system, and mental constraints. Utilizing the shared situational awareness theory of the DSA model, these aspects are then shared throughout the system, each interacting with each node, ultimately effecting their performance in the task. Therefore, the research question is pictured in Figure 21, with degrees of situational awareness within each analyst, and the aspects effecting that situational awareness between the two analysts, impact the performance of the team.

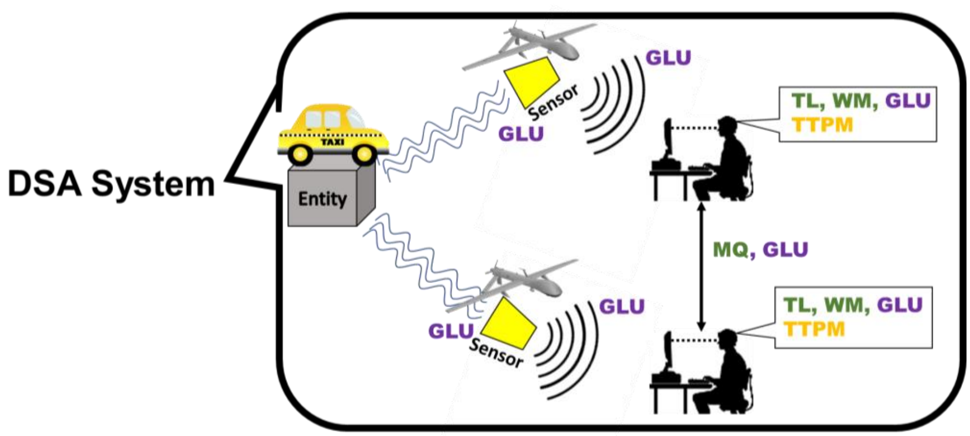


Figure 21 Baseline construct for the experiment

With the first experiment creating a baseline, this work postulates that variations in human communication performance (Message Quality (MQ)), based on the level of training and voice communications, will impact the other variables of the model and nodes within the system and overall SA of the team. Since training impacts the communication and SA of the team (Patrick and Morgan 2010; Seppänen et al. 2013; Sorensen and Stanton 2013, 2016), this work will demonstrate a positive correlation between verbal communication proficiency and performance outcomes. With higher verbal communication skills producing significantly better results than lower verbal communication skill levels.

Utilizing the fundamentals of visual analytics, this work will provide evidence that demonstrates an automation of the performance task utilizing Aided Target Recognition (AiTR) technology. This would be of importance in situations when teams are quickly formed to accomplish a task, that are unable to train prior to the execution. Since this would probably result in low verbal communication proficiency levels, this work will propose another solution utilizing the technology solutions with the AiTR field. Experiments run in this work will utilize a form of AiTR that will remove, or significantly reduce, the verbal communication (and subsequent GLU effects) which will result in levels of performance significantly equal or better than the best performance outcomes from the baseline.

As stated by, Johnson and Hanson (2011) the goal of visual analytics is to identify the best automated processes for the task at hand, estimating limits that can't be further automated, and then develop a tightly integrated solution that adequately integrates the top automated processes and human performance methods into a cohesive methodology.

3.3. Hypotheses

This work will explore the following hypotheses:

H #1: Given a DSA model, with three levels of Situational Awareness (SA), each level of SA will be significantly different than the other levels. This will be supported by the statistical analysis between large sets of results for each level of SA. Each level of SA will consist of stable dependent variables within the model representing WM, TL, and the function of GLU based on time. However, the dependent variables representing SA, with the main variable representing differing communication performance metrics, will impact the dependent variable represented by the number of seconds a target is detected and identified within the scenario. These SA metrics will be banded within a low, medium, and high category which will have a corresponding numerical value associated with the CPT values in Table 1.

This value will be incorporated into the simulation and 500 iterations will be run for each category level. Low communication metrics will correspond to very poor communications between analysts and overall poor SA of the identified entities to be tracked (pick-up truck). Each higher category will indicate more successful communications, corresponding to more training, and higher metric of communication success between analysts.

H #2: Given the baseline established from the first hypothesis, an additional data set will be created utilizing AiTR technology. The best performing SA level from the baseline will be significantly different than the results utilizing AiTR. This will be supported by the statistical analysis between the two data sets. The AiTR data set will be created by assuming a team with low SA metrics will be augmented with AiTR hardware and software. This technology, placed into the DSA model, will remove the requirement to verbally communicate between human analysts and will replace it digital communications tied to algorithms that assist in detecting specific entities and reducing human incorporated GLU through automation. This should negate the low communication performance metric that effects the SA level from baseline results. This model with AiTR is shown in Figure 22.

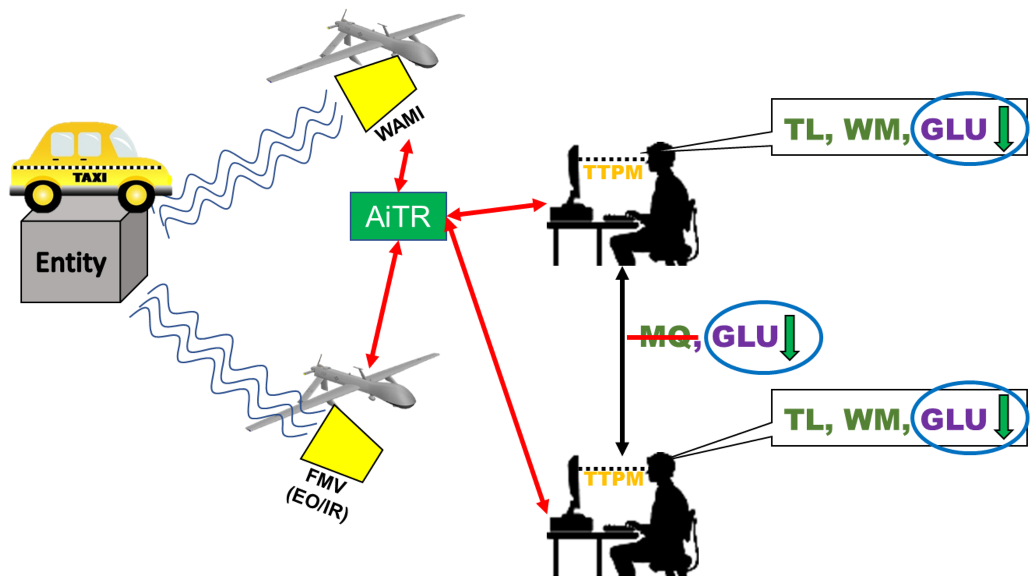


Figure 22 DSA Model with the incorporation of AiTR technology at the human operator's computer system

Due to the automated exchange of location through a digital and computerized medium, through the technology consisting of the AiTR, the message quality (MQ) between the two analysts will be removed, as shown in figure 22. This will reduce the overall geographical location uncertainty by removing the incorporation of GLU from the human analysts. 500 iterations will be conducted with these new metrics and compared to the highest performance results from hypothesis #1.

3.4. Expected Scientific Contributions

Research from this work will provide a DSA model, that incorporates cognitive attributes, that can predict the task performance of detecting and identifying a specific entity based on the level of training of the teams. It will also provide evidence that supports the use of technology that aided in target detection and identification through automation and how it can negate poor training of teams. As stated in section 1.6, this research contributes the most to those organizations where location and time are utmost important to their primary tasks. Additionally, it will provide these organizations research on the effect that communications (message quality) and situational awareness has on this task of identifying a specific entity (yellow taxicab). Therefore, this DSA model could be used in the fields of remote sensing, system and team performance analysis, and also in the acquisition of new technologies. It distinctively combines exact technological models of specific aerial vehicles and optical sensors with human performance models, which incorporate mental capacity metrics, to measure the cognitive ability of a human operator on a particular task based on training. Additionally, with the incorporation of geographical location uncertainty in this DSA model, a methodology of how GLU impacts performance of a system can also be evaluated. All these variables contribute to the end state of how well a team of humans can complete the specific task of detecting and identifying a specific entity within a complex urban environment.

The second hypothesis will specifically evaluate the trade-off between training and technology. It will provide evidence on how much technology can improve performance results within the constraints of this model and specified variables. For those organizations that rely on finding a location or entity as quick as possible, this research will present a potential technological framework that automates this process as much as possible (in an aided manner – not automatic). Especially when teams don't have time to train on communication skills – a consideration organizations might have to make when time and resources are limited. Additionally, this will provide a framework to predict performance of a team with variable degrees of communication skills and SA. Linking this improvement in the removal of geographical location uncertainty that can be spread within the model, it will provide additional research on the impact of GLU in human and non-human entities and its impact on collaborative efforts in location accuracy. Ultimately, this research will provide solutions to improve performance on the "Yellow Taxicab" problem from Chapter 1 – finding solutions to the problem in order to to solve it faster and more accurately. With solutions based on highly trained teams (with higher SA) or with AiTR technology that provides the same benefit as training.

4. MATERIALS AND METHOD

4.1. Utilization of Modeling and Simulation

Other than the prohibitive cost of actually setting up an experiment with all the vehicles, sensors, communications equipment, and personnel, this work will utilize a set of models and simulation engines to replicate the experimental environment. The main reason to use a simulation is that based on the models utilized, it is possible to explore multiple factors in fully controlled environment (Amaran et al. 2014). For this work, weather and all other environmental conditions will be removed to simplify the experiment. In this simulated environment, all vehicles and equipment can be programmed work at designated performance levels while the dependent variables of the experiment are changed for different iterations. This allows the isolation of independent and dependent variables so an optimized model can be determined.

Another reason for utilizing a simulation is the difficulty in setting up and approving a human-based experiment. This would be costly as explained previously, but would require significantly more time to prepare and execute as training, coordination, and the timeline required to incorporate live performers would make this experiment. A simulation also allows exponentially more iterations of an experiment that keeps most of the independent variables stable so the dependent variables can be accurately evaluated.

Research also supports the use of detailed scenarios to simulate high levels of psychological complexity for crew planning and execution tasks, including criterion stressors such as time pressure and information overload. Evidence supports this even when physical fidelity in the scenario is low (e.g. consisting only of a desktop computer and multiple monitors) (Prince and Jentsch 2001; Noble 2002; Toups et al. 2011; Hamstra et al. 2014).

For example, a program is described by Stout et al. (1998) on research investigating low physical fidelity training simulation. This experiment evaluated multiple two-person military aviation crews on the success of low physical fidelity simulated training through the performance on certain communication and SA tasks. The low physical fidelity training simulation consisted of two networked desktop computers and communications via intercom, and not an expensive aviation simulator or live flight training. Evaluation was conducted on the crew through interdependent tasks, emphasizing team skills such as mission analysis, communication, leadership, adaptive performance, situational awareness, and shared decision making. Results indicated that low fidelity training simulations were significantly comparable to more expensive training methodologies when comparing these cognitive skill sets.

Similarly, in a review of 58 studies concerning training on communications and SA by Fiore and Salas (2004) concluded that findings support the use of low-physical fidelity simulators for communication and SA training and that this training has led to positive attitudes, learning, and behavioral changes on the job. Recently, there has been burgeoning research on simulation-based training in health care settings. As with emergency response and military teams, members of health care teams typically have different areas of expertise, and teams operate in ambiguous, dynamic environments in which problems may have multiple possible solutions and require rapid decision making based on communications and shared SA. Studies in health care have come to many of the same conclusions as research in aviation and other military tasks or settings regarding assumptions about how simulated, low physical fidelity and the need to apply learning principles to the design of simulation-based training is very important (Graafland et al. 2012; Norman et al. 2012; Mcrobert et al. 2013; Salas et al. 2013; Hamstra et al. 2014; Benishek et al. 2015).

4.2. Creating a Simulated Environment

In order to create the baseline required for this research, the experiments require a simulation environment that is capable of accurately replicating the aspects that affect the detection and identification of a specific entity. The simulation would need to have the capacity to replicate the DSA model will integrating geographical location uncertainty, human communication performance, the human visual system, mental constraints, and the physics based operational properties of the aerial platforms and their associated sensors. The Fusion Oriented Command, Control, Communications, Computers, and

Intelligence (C4ISR) Utility Simulation (FOCUS) engine's basic functions can support most of these requirements and with some minor alterations, that will be discussed later in this work, can meet all of them.

4.2.1. Fusion Oriented Command, Control, Communications, Computes, and Intelligence (C4ISR) Utility Simulation (FOCUS) - the Simulation Engine

FOCUS was developed by the U.S. Army Material Systems Analysis Activity (AMSAA) to utilize authorized engineering models of platforms and sensors in order to analyze C4ISR's impact on tactical decision making (Harclerode 2015; AMSSA 2019). It is designed to simulate the performance of C4ISR systems and to permit rapid analysis and interpretation of simulation data for research or operational analysis. With the ability to simulate events down to platform-level resolution (vehicle, aircraft, dismounted soldier, etc.) it also replicates the behaviors of these platforms and also the targeted entities such as movement, collection, acquisition, and communications in robust code modules that can predict overall performance of C4ISR systems of systems (Jones et al. 2011).

This simulation was specifically built to simulates surveillance and reconnaissance processes, including sensor performance, tasking and collection; the exploitation and processing of data from all sources, the fusion of this information into tracks, and the communication of current predicted tracks to a visual simulation of entities and events in a three-dimensional battle-space.

It was designed to represents entities at the platform and sensor level. Behaviors such as movement, collection, acquisition, and communications are defined for each entity by the user when setting up the vignette. These behaviors can either be manually generated or by constructing a flow diagram of built-in, autonomous tasks along with dynamic conditionals and events (Jones et al. 2011; AMSSA 2019).

It has its own terrain database with low to high resolution terrain. It also includes a post-processing analysis toolkit is integrated into FOCUS to filter the output file and extract the desired results. The results can be viewed using the internal FOCUS graphs or exported for further spreadsheet analysis (AMSSA 2019).

Utilizing chronological, physics-based algorithms, FOCUS was designed to calculate and then analyze the capacity of a sensor to capture an entity within its Field of View (FOV) (AMSSA 2019). This algorithm incorporates multiple factors from the distance and speed of the platform carrying the sensor, to the angles between the sensor and targeted entity. It then calculates the probability of capture every second of the simulation. These results are then calculated with a corresponding TTPM table for the specific sensor to determine the probability of a human operator to detection and/or identification a specific entity within the captured image (Boettcher et al. 2010). This probability is based upon the distance, size, and other characteristics of the entity. To simplify the calculations, probabilities are based on the engineering models from a library of platforms and different sensors and the TTPM. Outcomes can be presented in several ways, but is based on the how long an entity was detected, identified, or tracked during a simulation's duration. This is demonstrated in Figure 23.

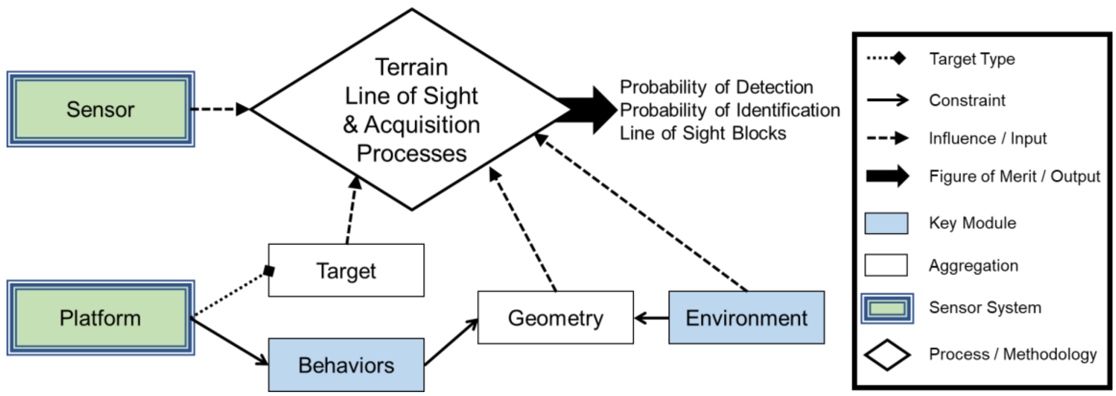


Figure 23 FOCUS Process diagram. Source (Burghardt et al. 2015).

FOCUS uses a sensor system (sensor and platform) in conjunction with the environment, platform behaviors, and target object to create a different set of figures of merit or output (task performance). Each terrain point or potential target, within the footprint of the sensor or field of view, is evaluated for each platform location to determine line of sight and probability of detection and identification of the specific entity or all entities within the field of view. The output, or figures of merit, include an average probability of line of sight / detection / identification for the terrain and platform locations (Harclerode 2015; Burghardt et al. 2015; AMSSA 2019).

4.2.2. Validation of the FOCUS model and Availability

Since FOCUS was created by AMSAA, this is the first public research that will utilize this program. As per Army Regulation (AR) 5-11 Management of Army Modeling and Simulation (M&S) (2014), Verification and Validation (V&V) is required for all Army M&S programs. In this regulation, "verification is the process of determining that the M&S accurately represents the developer's conceptual description and specification. Validation is the process of determining the extent to which the M&S is an accurate representation of the real world" (2014). This V&V was conducted by Burghardt et al. (2015) of FOCUS in which they conducted a comparative sensor performance analysis on Electro-Optical/Infrared (EO/IR) sensors. However, as this is a propriety program, not all aspects of the V&V are public. The report that Burghardt et al. conduct in Technical Report 2015-34 was reviewed by me. This report provided the necessary evidence I required to ensure that my experiments would be using a valid and verified simulation and authoritative models.

Concerning the actual V&V, part of the report goals was to ensure the sensors accurately interacted with terrain, environmental conditions, vehicles, objects, and other entities that exist within a complex environment. Finally, they conducted tests to ensure all the sensor modules (engineering models) and the simulation evaluated the ability of different sensors and platforms to detect, identify, and track specific entities in a real-world vignette.

The results of the test verified all algorithms and methodologies, specifically the TTPM, incorporated into FOCUS that represents entities at the platform level (e.g. aerial vehicles) and at the sensor level (e.g. EO/IR sensors) with respect to behaviors such as movement, collection, acquisition, and communications. For review of these results, requests should be made to Director, US Army Materiel Systems Analysis Activity, 392 Hopkins Road, Aberdeen Proving Ground, MD 21005-5071 to request Technical Report No. TR-2015-34 (Burghardt et al. 2015) The software for FOCUS is free of charge, but requests should also be made to the same address.

4.3. Modeling the Different Aspects of the Research Question

This work will utilize the simulation FOCUS to set-up and run the required experiments. This section begins with an explanation of the equations used in the experiment and followed by more explanation on how the simulation FOCUS utilizes the data used in the experiments. Data for the experiments is based off of the information provided with authoritative FOCUS database on both the platforms and the sensors. Sensor data is based off of the TTPMs established for each sensor that is inherent in the simulation (see section 2.8).

As a baseline in execution for each experiment, the target entity (yellow taxicab) is stationary within the starting point at the beginning of each iteration of the experiment. This location is hidden from all sensors and the entity cannot be detected until it leaves the facility. Once the simulation clock starts, the target entity will randomly leave the facility based on a random number generation between 0 and 300 seconds. Upon exiting the start point, the target entity will follow the same path and at the same speed for every iteration. However, this random departure will place the platforms and sensors in different locations on the map. Combined with the masking of the buildings, the first detection of the target entity will occur randomly for each iteration. Also, this means that each iteration will have different angles between the target entity which will place different buildings within the line of sight of the sensor and target entity. Intent for this random start time is to reduce any detection and identification anomalies that might occur due to beginning positioning of the platforms and entities. This will also create a wide variation in the results as some iterations might be masked by buildings for most of the timeframe, resulting in lower performance numbers.

4.3.1. Replicating the Platforms, Entities, and Sensors

In FOCUS, platforms are entities representing a particular individual piece of equipment. To accurately represent this entity, the model must maintain real-world physical attributes (signatures) for each platform in addition to performing realistic movements in accordance with different terrain. According to verification and validation analysis conducted by Burghardt et al. (2015) and verified by me from the report(Jones et al. 2011; Burghardt et al. 2015; AMSSA 2019), all characteristics of the platforms are represented accurately.

These characteristics have been recorded by previous experiments (Burghardt et al. 2015) and are accurately incorporated into the FOCUS database. Specifically, for this experiment, the MQ-1C Extended Range Multi-

Purpose (ERMP) UAS, commonly named Gray Eagle, is utilized for the sensor carrying platform, and a standard, yellow taxicab is the specific entity that the sensors system will detect and identify.

The sensors utilized in this experiment is categorized under Electro Optic / Infra-red (EO/IR) (see section 2.10). Burghardt et al. (2015) and I verified from this report that the sensors in the database specify that the following characteristics are the essential sensor parameters necessary for a valid representation:

- FOV Modes
    - Acquire-Targeting Task Performance Metric (TTPM) Shortcut Tables
    - Horizontal and Vertical Angles [degrees]
    - Magnification
- Gain Parameter (IR only)

For this experiment, I chose to use the MQ-1C platform, MX-20 High Definition FMV EO/IR sensors and the Redkite WAMI sensor (see section 2.10). I have spent many years utilizing and researching these platforms and sensors. This knowledge of these systems allows me to rapidly verify and understand the output that FOCUS is producing off of these systems.

Within the experiment, one MQ-1C platform equipped with the MX-20 High Definition (HD) Fully Motion Video (FMV) EO/IR sensors will be utilized for identifying the entity within its narrow Field of View (FOV) (see section 2.10.1).

Another MQ-1C equipped with the Redkite, lightweight Wide Area Motion Imagery sensor will use its sensor to detect entities within its large FOV. The FOV for both sensors depend on its magnification. FOCUS can change the magnification when the entity is located within its FOV. For the MX-20 EO/IR sensor, the sensor will begin at a wider FOV, and FOCUS will move it to a narrower FOV once the image is detected for identification purposes. The RedKite sensor will remain at a wider FOV since its responsibility is to detect entities (see section 2.10.2).

Utilizing the EO/IR sensors in FOCUS, there are several assumptions that must be accepted. The first is that the Acquire-Targeting Task Performance Metric (TTPM) is a valid representation for determining probability of detection/identification. Second, the default Field of View (FOV) used is the widest that has a probability of detection (P(d)) for a vehicle target of at least 0.7 unless otherwise set by the user. Third, the time limited search methodology is a valid representation of timing considerations for search and target acquisition processes. Fourth, each sensor has a dedicated human operator/analyst. Fifth, FOV is be defined by a horizontal and vertical angle. Sixth, the sensor stays centered on target when tracking (Burghardt et al. 2015).

4.3.2. Building the Terrain

FOCUS has the ability to represent real world terrain data and other various environmental conditions and entities in order to accurately simulate vignettes that replicate real-world events for studies. Environmental parameters, buildings and terrain data, along with its coordinate conversion within the model, were verified and validated in accordance to real world data (Jones et al. 2011; Burghardt et al. 2015; AMSSA 2019).

For this work, the simulation terrain data came with the FOCUS program, which was extracted from the National Geospatial Agency (NGA) geographical data (high resolution) repository which is within the terrain database within FOCUS. To acquire this terrain, contact the Director, US Army Materiel Systems Analysis Activity, 392 Hopkins Road, Aberdeen Proving Ground, MD 21005-5071. Similar LiDAR maps can be downloaded from other sources, and there are other terrain models within FOCUS (e.g. Fallujah, Iraq). These sources include the NOAA data access viewer (2019b) or from the United States Geological Survey (2019).

Samarra is a city in Iraq, approximately 78 miles north of Baghdad on the Tigris River (as depicted in Figure 24). In 2004, the city had an estimated population of almost 214,100 (Tesch 2019, c).

Figure 24 City of Samarra within the borders of Iraq. Source (BBC News 2007)

Samarra is known for its historical, religious sites to include the Great Mosque of Samarra. Most of the city's economy is based on tourism and academic / archeological studies with little industry. I chose to use it in this experiment since it was already cleaned up and ready for experimentation based on previous research by AMSAA. This allowed a quick access to an urban terrain that could be readily incorporated into FOCUS without additional work. The terrain database was created in 2004 from the collection of LiDAR scans from military platforms to develop a detailed map of downtown Samarra as depicted in Figure 25.

Figure 25 View of the section of Samarra that was mapped with LiDAR and used in this work. This is a 8x5 km rectangle. Source (Google Earth 2019).

This area consists of tightly packed multistory buildings (3-4 story) with narrow streets and larger intersecting wide avenues as depicted in the LiDAR image in Figure 26.

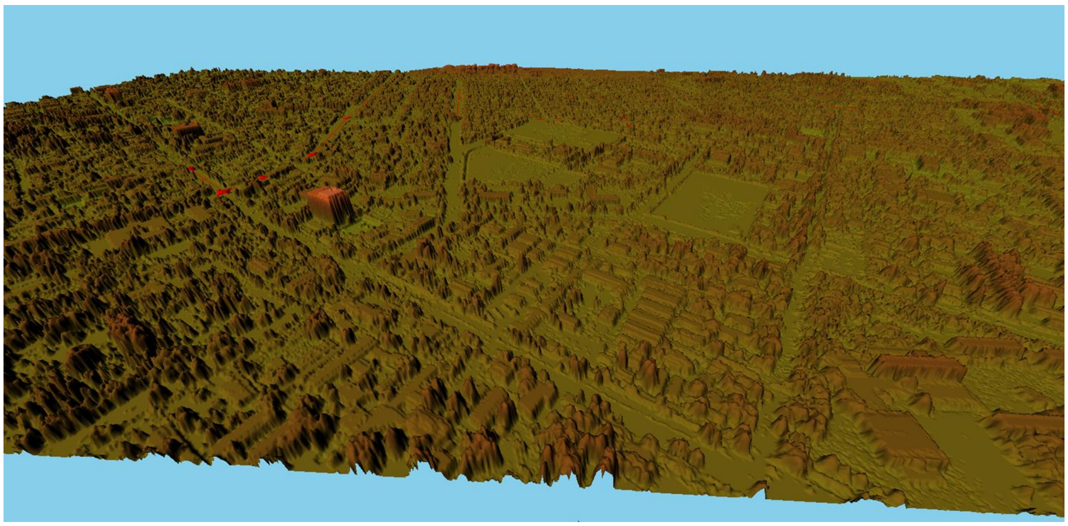


Figure 26 LiDAR picture of downtown Samarra, Iraq viewed in the FOCUS simulation. Source FOCUS.

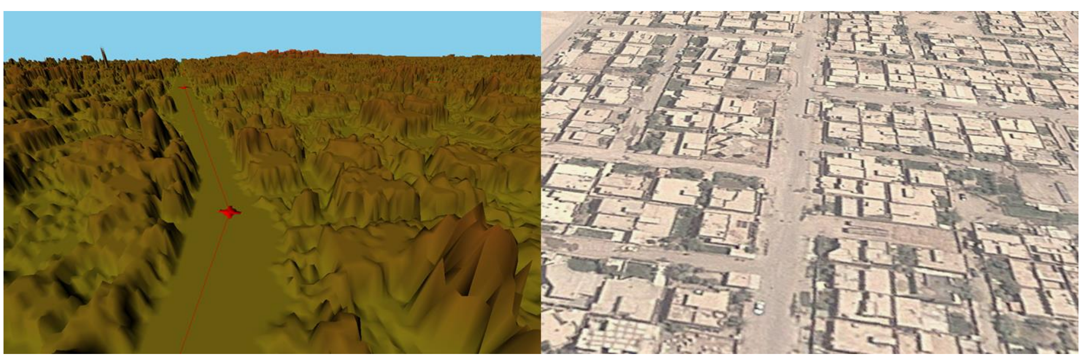


Figure 27 View of a street along the target's route as seen in LiDAR (Source FOCUS) and approximately the same image from Google Earth (2019).

As seen in Figure 27, visual buildings are not imported into the simulation to reduce computing requirements. LiDAR has captured the rough size, height, and shape of the buildings and in FOCUS have the ability to block the signal emissions so sensors cannot detect entities that are shadowed by the buildings. For this work, the details of the building are irrelevant. Their rough size is required in order for them to create line of sight blocking between the specified entity and the sensor (on the platform). This is a common problem in urban terrains (Williams et al. 2014). Therefore, the basic LiDAR imagery meets the objects of the terrain for this experiment, to block the line of sight between the sensor and target entity depending on the angle and location of each entity in the scenario. This replicates a real-world vignette for this experiment.

According to the U.S. Bureau of the Census (1994) , an urban area is defined as a continuously built-up area with a population of 50,000 or more people. Additionally, the U.S Census Bureau (1994) would classify Samarra as a metropolitan area or city; however, it size is in the small category (<250,000). Samarra wasn’t picked because it is an ideal candidate for this research, it was chosen because it provides the foundational urban environmental conditions I wanted for the experiments.

In order to make the urban environment more complex, additional vehicles are added to the map in order for the analysts to distinguish between different vehicles. Even though Samarra wouldn’t have vehicular traffic as in a developed world, additional vehicles were added to this map to create a more complex environment with higher traffic density for this experiment. According to the Highway Capacity Manual (2014), Traffic density is defined as the number of vehicles occupying a unit length of roadway. Optimum density is normally around 36 to 48 vehicles per lane mile. There are approximately 60 miles of roads within the 24 miles^2 of the LiDAR model of Samarra. 2,880 vehicles are moving on these roads, providing a density of 48 vehicles per miles, which is heavy, but free flowing traffic (Roby 2014) An additional 9,363 vehicles are parked within the city, along the roads, within parking lots, or other locations, for a total of an additional 12,243 vehicles were added to the map. This incorporation of vehicles and traffic creates conditions of a busy, complex urban environment with vehicles, moving and stationary, within the boundaries of the terrain. The intention of this addition was to increase the complexity of the environment and to create a more difficult detect and identification field for the operators.

At the start of the simulation, half of these vehicles will begin to move along designated routes, while the specific entity, or target in this scenario, will begin traveling along its route. The intent of these vehicles is to create the background clutter that a human operator must shift through (moving and unmoving) in order to find the specific entity. Additionally, these additions replicated a traffic pattern of a busy city with flowing traffic (Deaver et al. 2009; Elliethy and Sharma 2016). Due to the limitations of the program, no pedestrians were incorporated and no traffic regulation technologies (e.g. traffic lights) were incorporated into the simulation. All traffic continuously flowed with vehicles continuously starting and stopping on their assigned routes without an hinderance. Additionally, the simulation is unable to replicate collisions so all entities passing through each other (but not the buildings). Hypothetically, this could make detecting and identification a vehicle more difficult, but the impact of that variable is not addressed in this experimentation.

4.3.3. How FOCUS Detects and Identifies a Specific Entity

EO/IR target acquisition performance is measured using the Acquire-TTPM model, which determines a probability of detection and identification between a sensor and a target (Burghardt et al. 2015). As described by Hixson et. al (2017), Acquire-TTPM was designed to reduce a simulation's computational requirements during large scale testing and evaluation events while still supporting the TTPM. Acquire-TTPM utilizes precomputed tables for specific sensors based on scene conditions and three coefficients that can be easily referenced by the simulation. FOCUS utilizes Acquire-TTPM through these three equations (Hixson et al. 2017).

Equation 6

$$\boldsymbol{X_{min} = \frac{X_1}{\omega} + X_2}$$

Equation 7

$$\boldsymbol{A = \frac{L_1}{1 + A_1 \omega^{A_2}}}$$

Equation 8

$$Acquire - TTPM = A\left(\left|C_{tgt}\right| - X_{min}\right)^{B}$$

Equation 6 determines the value of X_{min} which represents minimal size of the target needed to detection. Equation 7 determines A, which represents the eye angle correction. Equation 8 is the updated Acquire TTPM values which is a function of the contrast of the target (C_{tgt}) - calculated by FOCUS X_{min} (minimal size of the target at a specific distance), and A (eye angle correlation). A_1, A_2, X_1, X_2, B, and L_1 = sensor specific calculated parametrized values based off numerous iterations of calculating the TTPM and fitting results to the form. ω is the value of the angular size of the target, calculated by FOCUS.

Building the Acquire-TTPM tables requires these calculations to be run for each sensor in order to determine the CTF function. Then this function is used to create the tables utilized by FOCUS (Harkrider et al. 2014). he Acquire-TTPM implementation for each EO/IR sensor type (MX-20 (EO/IR), RedKite (WAMI)) maps back to an authenticated engineering level model. The Acquire model is a rolled-up version of the engineering level model that is less computationally expensive and more appropriate for real time simulations. Acquire-TTPM is a validated model backed by empirical data and is the U.S. Army standard for EO/IR target acquisition performance (Gerhart 1996; Hixson and Teaney 2016; Hixson et al. 2017). Within FOCUS, the Target Acquisition Draw Methodology (TADM) is used in conjunction with the Acquire-TTPM output to decide whether or not a target is detected. The TADM was altered in FOCUS to not allow false or bad draws of percentages in order to prevent a single target entity or single sensor from becoming incapable of being detected or making detections. These bad draws would create a mathematical problem (e.g. zero in a denominator) or other forms that invalidate the data and create either the simulation to fail or zeros out a probability based on the limitations of the. The change is that the observer/target draw is redrawn for each detection opportunity and results are based on the probability of detection and identification of the Acquire-TTPM (Teaney and Reynolds 2010; Maurer et al. 2013). These results are incorporated into a table (see Table 2 below) for every sensor that is utilized by the FOCUS program.

As a validated standalone model, Acquire-TTPM data is based on empirical data from perception experiments of trained experiment subjects finding targets in EO/IR imagery (Burghardt et al. 2015). FOCUS has an Acquire-TTPM database for every sensor that captures the probability of detection or a probability of identification based on the slant range between the sensor and the targeted entity. As defined by FOCUS, the slant range is the direct line, in meters, between the aerial platform and the terrestrial target entity.

In the FOCUS Acquire-TTPM database, this probability is represented as P(inf) to indicate the probability of completing the performance task if given infinite time with a single image. This is the baseline that FOCUS uses to calculate the probability of task completion for every second of the simulation scenario length as a function of range (Burghardt et al. 2015). As depicted in Tables 2 and 3, the probability of completing the task (detection or identification) is a function of the slant range (distance between the aerial platform and ground based targeted entity). As the range increases, the probability of success decreases. The minimum range used in this work is 2500m, since that is the minimum height the MQ-1C platforms will fly. If the platform is directly above the target entity, they will have a slant range of 2500m. Since the Acquire-TTPM is based on the TTPM, the initial data was calculated utilizing a 50% probability of success within TTPM, as depicted by V50 in Equation 5. Using that value, the range is then calculated. This is why the 0.5 probability has a unique slant range that is not rounded as the other ranges. FOCUS and Acquire-TTPM then calculate the remaining ranges based off this 0.5 probability. This capability will be used later in this work when incorporating other factors that will impact the TTPM value. For this work, the base data for the FMV and IR sensors are in Tables 2 and 3.

Table 2 Acquire- TTPM data for the MX-20HD FMV sensor extracted from FOCUS for probability of detection and identification. With the sensor as 2500m, P(inf) is the probability of detecting or identifying the specific entity at a distance of Rng (meters) given infinite time.

Detect on MX-20 HD FMV Altitude 2500m			Identify on MX-20 HD FMV Altitude 2500m	
P(inf)	Rng (meters)		P(inf)	Rng (meters)
0.982	2500		0.500	2500
0.949	3000		0.490	2566
0.878	3500		0.372	3000
0.778	4000		0.264	3500
0.664	4500		0.186	4000
0.549	5000		0.132	4500
0.500	5228		0.094	5000

Table 3 TTP metric data for the MX-20HD IR sensor extracted from FOCUS for probability of detection and identification. With the sensor as 2500m, P(inf) is the probability of detecting or identifying the specific entity at a distance of Rng (meters) given infinite time.

Detect on MX-20HD IR Altitude 2500m			Identify on MX-20HD IR Altitude 2500m	
P(inf)	Rng (meters)		P(inf)	Rng (meters)
0.999	2500		0.750	2500
0.999	3000		0.691	3000
0.999	3500		0.610	3500
0.999	4000		0.535	4000
0.999	4500		0.500	4272
0.998	5000		0.471	4500
0.500	12222		0.414	5000

The main difference in this base data is that the probability of detecting a target entity is significantly higher than identifying it. This is due to the additional cognitive resources and time required to identify a specific entity over just detecting it. This is based on research utilizing subjects to detect and identify entities on computer monitors as detailed in the TTPM section, section 2.8 (Vollmerhausen 2004; Preece et al. 2014).

4.3.4. Updating the Methodologies in Finding and Identifying an Entity

Given the initial methodology of find, fix, track, FOCUS needs to answer the "how" this is accomplished within its simulation. Compared to the Acquire-TTPM tables that is based on the probability to complete a task given infinite time, FOCUS requires an instantaneous result since there is a time constraint in the simulation. Additionally, in most experiments and situations, operators are required to detect or identify a target by scanning a Field of Regard (FOR) larger than a single imager field of view seen on a computer screen. In order to accomplish this task, FOCUS incorporates several methodologies described below (Maurer et al. 2013).

- Target Acquisition Draw (TADM): uses a weighted set of three random draws to account for variability.
- Step-stare search: approximates the human search process in a FOR as a series of individually interrogated fields of view (FOV). The FOR is searched from left to right, top to bottom.
- Time-limited search (TLS): this is the required, consecutive seconds of consecutive task performance (detection or identification) successes

for the task to be complete based on task difficulty as displayed in Table 4.

Table 4 TLS values based on Task Difficulty for Ground Vehicle Targets

<table>
<tr><th colspan="5">Ground Vehicle Targets</th></tr>
<tr><th>Acquisition Level</th><th>Target Dynamics</th><th>Thermal Clutter</th><th>V50 Visual</th><th>V50 Thermal</th></tr>
<tr><td rowspan="4">Detection</td><td>Stationary</td><td>None/Low</td><td>2</td><td>2</td></tr>
<tr><td>Stationary</td><td>Medium</td><td>2</td><td>6</td></tr>
<tr><td>Stationary</td><td>High</td><td>2</td><td>No Recommendation</td></tr>
<tr><td>Moving</td><td>---------</td><td>1.3</td><td>1.3</td></tr>
<tr><td>Classification</td><td rowspan="4">Stationary & Moving</td><td rowspan="4">N/A</td><td>7</td><td>7</td></tr>
<tr><td>Recognition</td><td>9</td><td>9</td></tr>
<tr><td>ID Call</td><td>11</td><td>11</td></tr>
<tr><td>Correct ID Call</td><td>13</td><td>13</td></tr>
</table>

With these methodologies, Acquire-TTPM is integrated into them in order to form a complete target acquisition process. As shown in Figure 28, FOCUS divides the Field of Responsibility (FOR), this covers the area the sensor is responsible for searching – established in the program of the simulation, into individual FOVs, or the viewable area of the sensor or optic placed displayed on a computer screen (Hixson et al. 2017). Each FOV is then searched, left to right and top to bottom. If FOCUS determines that the FOV has the target in it, and not obscured by terrain or objects, the probability is detected using the Acquire-TTPM based on the range model. It continues to calculate the probability of detection or identification compared to the weighted random draw calculated by using TADM to determine a final probability of target detection. Once calculated, FOCUS uses the TLS model to determines if the observer had time to detect the target. If enough time was calculated to detect the targeted entity, determined by TLS, FOCUS randomly determines if the target was detected (based on probability). If the targeted entity is determined to be detected, the next step is identification (Burghardt et al. 2015).

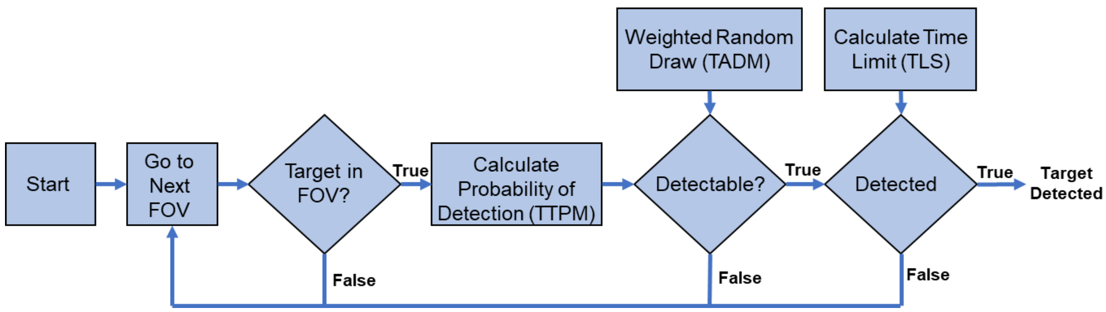


Figure 28 FOCUS Find and Fix (a.k.a detection) flowchart. Source (Hixson et al. 2017)

In order to determine if the detected entity is the targeted entity, FOCUS must apply the Find and Fix process in Figure 29 for identification. As with detection, the probability of identification is calculated utilizing the Acquire-TTPM based range model as presented in Figure 28. Compared to the same TADM draw for detection and the same TLS, the probability for identification is determined and tested. With a result of no identification, FOCUS will check if increased magnification is possible. If this possible, magnification is increased, resulting in higher probability of identification, and re-tested (Burghardt et al.

2015). Consecutive successes that meet the TLS values will result in a recorded success for identification of the target.

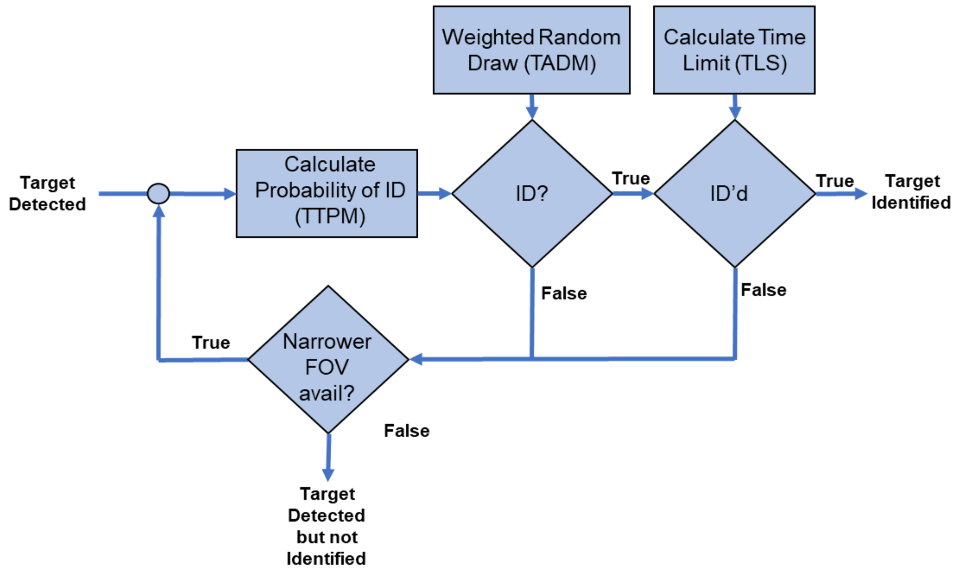


Figure 29 FOCUS Identification flowchart. Source (Hixson et al. 2017)

4.3.5. Incorporating Human Cognition Through Team Performance Communications into FOCUS

Since Acquire-TTPM contains probabilities of different aspects of EO/IR target acquisition, it determines the performance of a single human operator to detect or identify a target entity. In order for this work to incorporate team performance, the ability of two human operators to execute their assigned functions must be integrated into the model. This will require augmenting the Acquire-TTPM model with a unique addition of team performance based on communications found in the research of Ahmed et al. (2014). Utilizing these validated human performance models to replicate interactions and to determine the ability to predict system performance with multiple operators, especially as system complexity increases and its properties change over time. Incorporating additional technology will hypothetically reduce complexities in the system, thereby reducing the mental load for an operator which can improve their performance.

Augmenting the Acquire-TTPM model with Ahmed et. al. (2014) human performance model will incorporate more complexity the target acquisition system within FOCUS. Previous research (Bayrak and Grabowski 2006; Manoj and Baker 2007) have indicated that poor network reliability and variability in response time decreases human performance, compounding to larger system inefficiencies. Overall, as network complexity increases, which leads to more demands on the human operator, the whole system's performance starts to degrade (Artman and Garbis 1998; Cooke et al. 2005; McKendrick et al. 2014). These research studies support the hypothesis that as a system or networked system increases in complexity, which results in an intensification on the task load of the human operator, the overall efficiency and effective of the system decreases. Therefore, adding the value of this human cognition performance metric should reduce the Acquire-TTPM value utilized in FOCUS. The values that will degrade the Acquire-TTPM values are from Table 1. These values will be explained in subsequent sections.

4.3.6. Replicating Geographical Location Uncertainty (GLU)

The last variable that needs to be incorporated into this experiment's construct is imprecision in geographical location. As discussed previously, one method to account for all of the inaccuracies in geographical location is to model the uncertainty (Heuvelink 1998). For this work, the inaccuracies within the system have propagated to the first observer – the one trying to detect the entity or target. With the inclusion of the first human operator's errors, a level of uncertainty in location is communicated to the second observer – the one trying to identify the entity. For this scenario, the uncertainty is manifested through errors in positional accuracy. Therefore, the second human operator must detect and then identify a specific entity while working with the cumulative GLU from the first sensor all the way to their own internal, cognitive errors. FOCUS can replicate this in the function TLS with more difficult tasks requiring more time to complete the task based upon the difficulty level from table 4. For this work, the TLS will be impacted by the cognitive performance score from Table 1. As communications between the "Detector" and the "Identifier" degrade, the GLU will increase, resulting in the task difficulty to increase, and it will take longer for the "Identifier" to complete their assignment. In order to implement this into FOCUS and the experiment, the task difficulty in FOCUS will be altered to replicate the differences in the SA score based on the communication performance metric (Low, Medium, or High) from table 1. The result will be that these scores will increase the time (in seconds) required for task competition: 0.08 for High; 0.19 for Medium; 0.32 for Low. These values are presented in Table 5.

Table 5 TLS task difficulty scores based upon Cognitive Performance Score Degradation. Red indicates the scores used for this work.

Ground Vehicle Targets (High Cognitive Performance Score)				
Acquisition Level	Target Dynamics	Thermal Clutter	V50 Visual	V50 Thermal
Detection	Stationary	None/Low	2.2	2.2
	Stationary	Medium	2.2	6.5
	Stationary	High	2.2	No Recommendation
	Moving	---------	1.4	1.4
Classification	Stationary & Moving	N/A	7.6	7.6
Recognition			9.7	9.7
ID Call			11.9	11.9
Correct ID Call			14	14

Ground Vehicle Targets (Medium Cognitive Performance Score)				
Acquisition Level	Target Dynamics	Thermal Clutter	V50 Visual	V50 Thermal
Detection	Stationary	None/Low	2.6	2.6
	Stationary	Medium	2.6	7.7
	Stationary	High	2.6	No Recommendation
	Moving	---------	1.7	1.7
Classification	Stationary & Moving	N/A	9	9
Recognition			11.6	11.6
ID Call			14.1	14.1
Correct ID Call			16.7	16.7

Ground Vehicle Targets (Low Cognitive Performance Score)				
Acquisition Level	Target Dynamics	Thermal Clutter	V50 Visual	V50 Thermal
Detection	Stationary	None/Low	3.4	3.4
	Stationary	Medium	3.4	10.2
	Stationary	High	3.4	No Recommendation
	Moving	---------	2.2	2.2
Classification	Stationary & Moving	N/A	11.9	11.9
Recognition			15.3	15.3
ID Call			18.7	18.7
Correct ID Call			22.1	22.1

Since the time to complete the task increases as the SA level decreases, this will replicate the increase the time to communicate in FOCUS. This is due to the message quality being poor and the time to communicate the location of the entity takes a longer time to execute. While this explanation is occurring, the vehicle will continue to move and the GLU area will also increase in the simulation – increasing the difficulty of the second analyst, the “identifier,” to accomplish their task; therefore, GLU is directly related to the MQ. As the MQ decreases, it will increase the time it takes to communicate the location of the target, increasing the GLU within the simulation and ultimately reducing the performance value of the “identifier.”

4.3.7. Explanation of Experiment’s Structure

As explained previously, this experiment will utilize simulated entities within FOCUS to address the this works hypotheses. As depicted in Figure 30, which is a screen shot from the FOCUS program, the targeted entity moves within the simulated urban terrain, the detecting platform (MQ-1C UAS) with its RedKite WAMI sensor will fly over the terrain at optimal height, at a specified speed, and following a directed flight pattern (large oval). Its sensor will detect entities within its FOV and the “Detector” will attempt to identify the targeted entity once it leaves its Area of Interest (AOI) that is being continuously monitored by the Detecting Platform and Sensor.

Once a possible targeted entity is detected by the “Detector,” they will communicate the location of the potential targeted entity to the “Identifier.” The identifying platform is also flying at an altitude of 2000m, at a constant speed and following its own flight pattern (large “figure eight”) will then change its flight pattern to try and maintain a constant 2000m from the targeted entity.

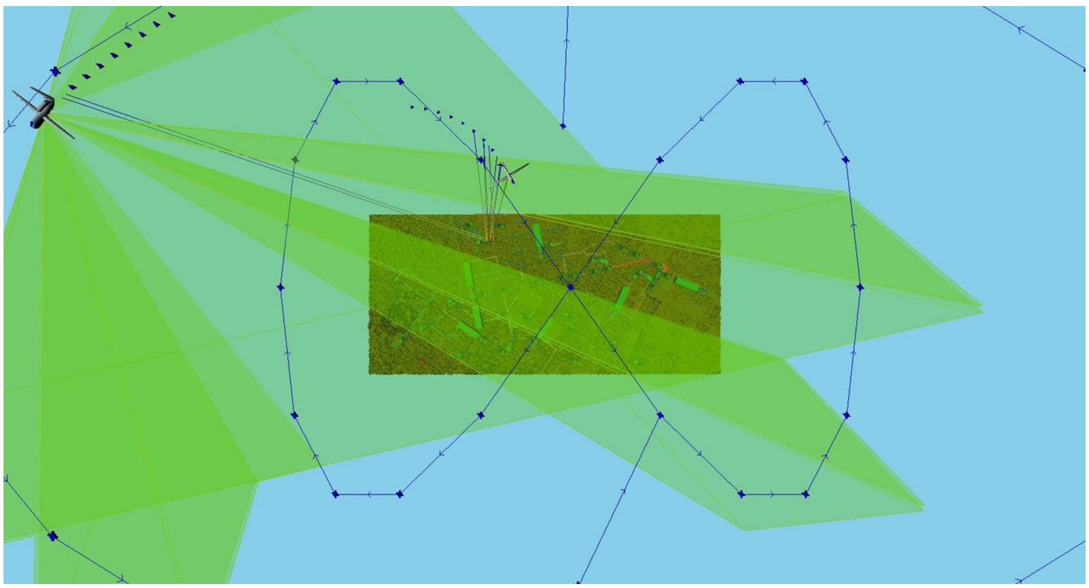


Figure 30 Screen shot from FOCUS depicting platform flight patterns and sensor FOVs

The “Identifier” will then search the location in order to detect the targeted entity communicated by the “Detector.” If the identification platform is not within range or the target is obscured by a building, the hand-off will not be made and the request will be dropped. However, the identification platform will move toward the target location in order to place the identification sensor within range. While this maneuvering is occurring, the target entity will continue to move along its designated route and the detection platform will continue to conduct detections. If the hand-off is made to the “Identifier” and the entity moves behind a building (based on the new angle and slant of the identifying platform) and the complete FOV is scanned without detection, this iteration will be labeled “lost” and the process starts again if the “Detector” is still tracking the targeted entity. If not, the search of the Field of Responsibility (FOR) by the “Detector” begins again.

If the targeted is acquired by the “Identifier,” they will try to positively identify that the potential entity is the actual targeted entity utilizing the MX-20 high definition video sensor on their own platform. Values for detecting and identifying are resident within FOCUS, but the detecting and identifying probability of the “Identifier” will need to be degraded through the TLS function based on values from Equation 6 due to the added complexity, variable levels of communication quality, incorporated into the process.

Therefore, the original value Acquire-TTPM value for detection will remain unaltered for the “Detector.” The Acquire-TTPM value for detection and identification of the “Identifier” will be degraded according the values in Table 6. Since these values for Y increase as the better values for TL, MQ, WM improve, there should be in inverse relationship with Acquire-TTPM. As the performance measure of cognitive ability for communication (value Y) increases, there should be less of an effect on Acquire-TTPM probabilities, as shown in Equation 9.

Equation 9

$$\textbf{Experiment TTPM = Acquire TTPM – (1-Y)}$$

Y = Performance metric for Cognitive Ability from Equation 1

FOCUS will ingest this information through the Acquire-TTPM tables within the program. Utilizing existing edit programs (designed within FOCUS), the Acquire-TTPM tables values from table 2 and 3 will be replaced with the Experimental TTPM with the following values from Equation 9.

Table 6 Experiment TTPM values that replace Acquire-TTPM

Detect on MX-20 HD FMV				
		Cognitive Performance		
		0.08	0.19	0.32
P(inf)	Rng	High	Med	Low
0.98	2500	0.90	0.79	0.66
0.95	3000	0.87	0.76	0.63
0.88	3500	0.80	0.69	0.56
0.78	4000	0.70	0.59	0.46
0.66	4500	0.58	0.47	0.34
0.55	5000	0.47	0.36	0.23
0.50	5228	0.42	0.31	0.18

Detect on MX-20HD IR				
		Cognitive Performance		
		0.08	0.19	0.32
P(inf)	Rng	High	Med	Low
0.99	2500	0.91	0.80	0.67
0.99	3000	0.91	0.80	0.67
0.99	3500	0.91	0.80	0.67
0.99	4000	0.91	0.80	0.67
0.99	4500	0.91	0.80	0.67
0.99	5000	0.91	0.80	0.67
0.50	12222	0.42	0.31	0.18

Identify on MX-20 HD FMV				
		Cognitive Performance		
		0.08	0.19	0.32
P(inf)	Rng	High	Med	Low
0.50	2500	0.42	0.31	0.18
0.49	2566	0.41	0.30	0.17
0.37	3000	0.29	0.18	0.05
0.26	3500	0.18	0.07	0.00
0.19	4000	0.11	0.00	0.00
0.13	4500	0.05	0.00	0.00
0.09	5000	0.01	0.00	0.00

Identify on MX-20HD IR				
		Cognitive Performance		
		0.08	0.19	0.32
P(inf)	Rng	High	Med	Low
0.75	2500	0.67	0.56	0.43
0.69	3000	0.61	0.50	0.37
0.61	3500	0.53	0.42	0.29
0.54	4000	0.46	0.35	0.22
0.50	4272	0.42	0.31	0.18
0.47	4500	0.39	0.28	0.15
0.41	5000	0.33	0.22	0.09

As discussed in section 2.8, the original 0.5 and unique range is the basis for how Acquire-TTPM creates the required tables in FOCUS. For each

Cognitive Performance value, the range for the 0.5 value is determined and FOCUS automatically fills out the remaining tables based on internal algorithms.

Overall, each iteration of the experiment will determine how many seconds a target was identified correctly (given how many times it was lost, blocked by building, or other factors that FOCUS replicates). During these series in FOCUS, Experimental-TTPM and the task difficulties of TLS will be grouped together into High, Medium, and Low Situational Awareness (SA) levels that support this DSA model. Each variation of SA (Low, Med, High) will be run 500 times in order to create a sufficient population. The table of each iteration result will then be statistically analyzed to determine if the hypotheses are supported or not.

4.3.8. Matching Experiments with Research Question

Referencing the hypotheses, the first step is to create a baseline that the remaining experiments will be compared against. This experiment will utilize FOCUS, in the scenario detailed previously, to execute 500 iterations for each dependent variable of the grouped SA level. The output from these iterations will be statistically compared to ensure that each is significantly different from each other.

The next step, and in order to determine the results for the second hypothesis, is to incorporate AiTR into the system. In Figure 35, the AiTR technology connects all other aspects of the system in this experiment and leverages digital communications to reduce the requirement to verbally communication the yellow taxicab's location. The effects is that the digital communications significantly decreases the effect of MQ resulting in an increase in probability to accomplish the required task. Referencing Table 1, the assumption for this experiment is that since it reduces the TL of the operator with relevant messages, the cognitive performance metric for the AiTR would be the 99% in the table. When this is applied to Equation 9, the results that would be incorporated into the Experimental-TTPM is in the following table.

Table 7 AiTR Experimental-TTPM values utilized by FOCUS

Detect on MX-20 HD FMV				Detect on MX-20HD IR		
Altitude 2500m				Altitude 2500m		0.01
P(inf)	Rng	High		P(inf)	Rng	AiTR
0.982	2500	0.982		0.999	2500	0.989
0.949	3000	0.949		0.999	3000	0.989
0.878	3500	0.878		0.999	3500	0.989
0.778	4000	0.778		0.999	4000	0.989
0.664	4500	0.664		0.999	4500	0.989
0.549	5000	0.549		0.999	5000	0.989
0.500	5228	0.500		0.500	12222	0.490

Identify on MX-20 HD FMV				Identify on MX-20HD IR		
Altitude 2500m				Altitude 2500m		0.01
P(inf)	Rng	High		P(inf)	Rng	AiTR
0.500	2500	0.500		0.750	2500	0.740
0.490	2566	0.490		0.691	3000	0.681
0.372	3000	0.372		0.610	3500	0.600
0.264	3500	0.264		0.535	4000	0.525
0.186	4000	0.186		0.500	4272	0.490
0.132	4500	0.132		0.471	4500	0.461
0.094	5000	0.094		0.414	5000	0.404

After conducting 500 iterations with this TTPM table, the results from the baseline would be compared to these results to determine if the hypothesis should be supported or not.

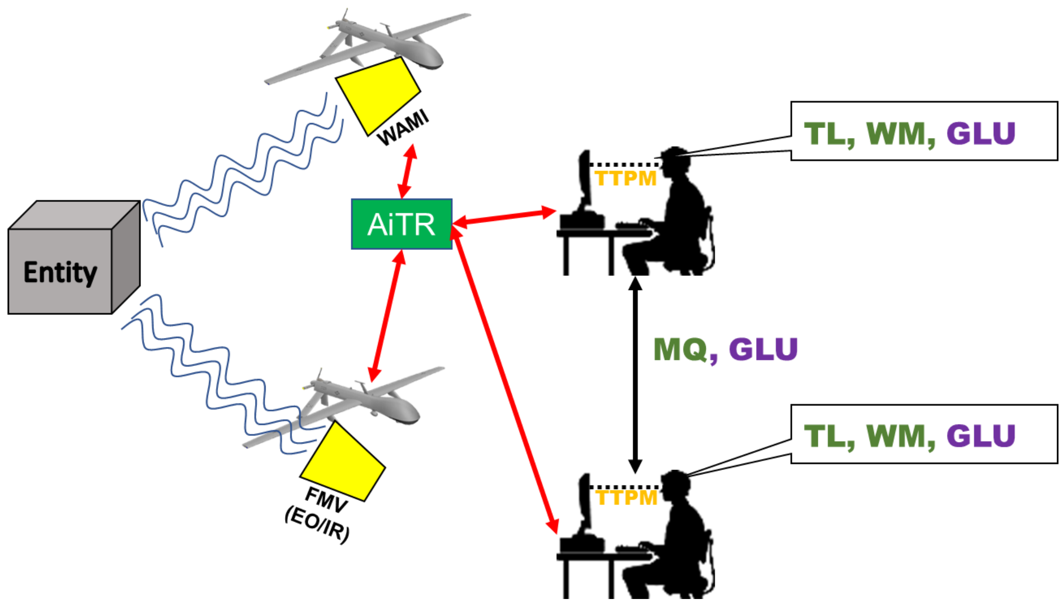


Figure 31 Incorporating AiTR into the system

5. ANALYSIS OF RESULTS

5.1. General Analysis Observations

After conducting 500 iterations for each level of Situational Awareness (SA) in the DSA model, the first step is to determine the correlation between the data sets. The correlation results for FMV SA levels are in Table 8 and the IR SA levels are in Table 9.

Table 8 Correlation results for FMV SA Levels

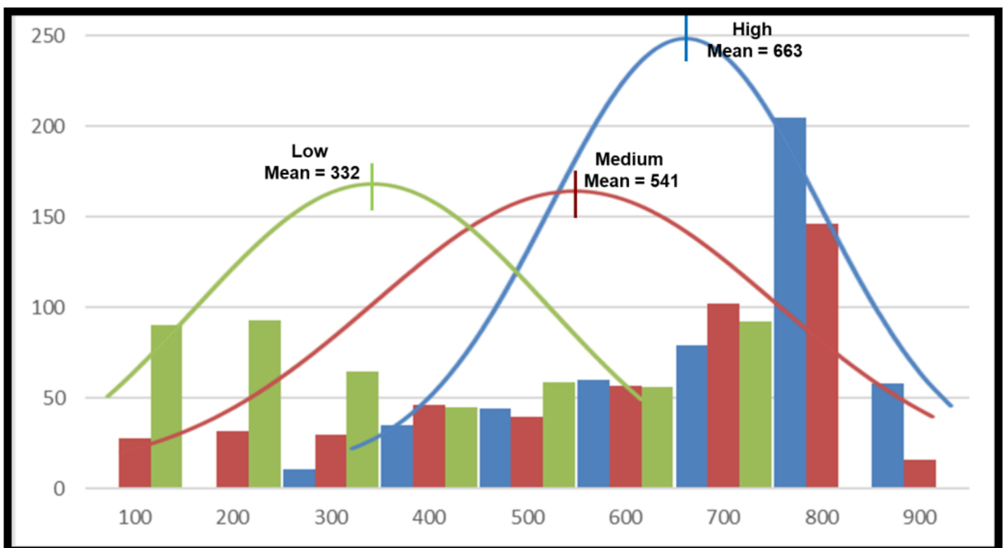
	high	*med*	*low*
high	1		
med	0.9981	1	
low	0.9239	0.9301	1

Table 9 Correlation results for IR SA Levels

	high	*med*	*low*
high	1		
med	0.9926	1	
low	0.9400	0.9686	1

Both tables indicate a very high positive correlation between the data sets. This indicates that the data is linearly similar and provides evidence that data collection between the data sets was normal, with not outliers or areas that need to be addressed prior to further analysis.

The next analysis step is to visualize the data through a stacked histogram (all three data sets) overlaid with a normal distribution bell curve of the data sets to visualize how the data compares to one another. Figure 32 compares the FMV SA data sets and Figure 33 compares the IR SA data sets.



SA Level Results	High SA	Medium SA	Low SA
Frequency Histogram			
Normal Distribution Bell Curve			

Figure 32 FMV SA Level Data Sets. Histogram and Normal Distribution Curve

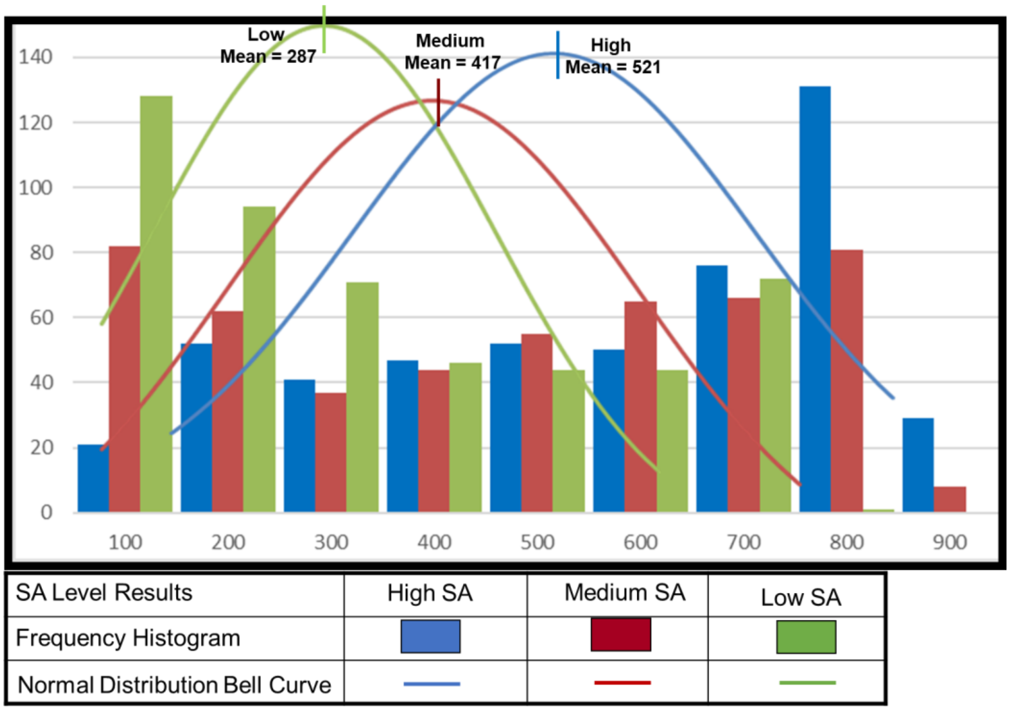


Figure 33 IR SA Level Data Sets.   Histogram and Normal Distribution Curve

Comparing the frequency of the histograms for FMV (Figure 32), both the High and Medium results have distributions are left-skewed and favoring the higher results, with the High results heavily left-skewed. The Low results are more bimodal but with more distribution at the lower results. However, this analysis supports previous research that as the SA increases, due to training, the performance results also improve. Low SA provided lower results and as the SA increased the distribution of the results skewed more heavily to the higher numerical results, not only in value (more seconds identifying a target) but also in frequency.

Analyzing the results for the IR sensor (Figure 33) also follows the results for the FMV sensor. However, the Lower SA was heavily right skewed with a higher proportion of the results in the lower numerical values. Medium SA results are more bimodal while the Higher SA results match the FMV High SA results and is left-skewed. However, the distribution of the three levels are much closer together for the IR sensor than was presented in the FMV sensor.

The more bimodal distribution suggests a transition in how the simulation calculated results. This transition is more pronounced in the IR sensor due to the right and left skewed distribution of the Low and High results. This transition seems to have occurred in the Low SA for the FMV sensor as the results markedly improve between Medium and High SA data sets. This might indicate a variable or set of variables that are heavily influencing the results of the simulation and warrants additional research.

Reviewing the descriptive statistics provides additional information on the analysis of the data. As indicated by the analysis on the histograms and normal distribution curves (Figures 32 and 33), the descriptive statistics of mean and mode follow the same trends as shown in Table 10. With numerically higher results for High SA over the Medium and Low SA results.

Table 10 Descriptive Statistic Results for different levels of SA, 500 Iterations

High Situational Awareness (SA)			
Infrared Sensor		***Full Motion Video Sensor***	
Mean	**487.36**	Mean	**619.60**
Standard Deviation	**236.56**	Standard Deviation	**145.46**
Median	529.00	Median	667.00
Count	500	Count	500
Medium Situational Awareness (SA)			
Infrared Sensor		***Full Motion Video Sensor***	
Mean	**417.10**	Mean	**541.31**
Standard Deviation	**253.75**	Standard Deviation	**223.08**
Median	452.50	Median	621.00
Count	500	Count	500
Low Situational Awareness (SA)			
Infrared Sensor		***Full Motion Video Sensor***	
Mean	**323.00**	Mean	**373.23**
Standard Deviation	**216.96**	Standard Deviation	**217.81**
Median	263.50	Median	345.50
Count	500	Count	500

For all the results in all the SA levels, FMV and IR, the standard deviation is high. This is supported by the analysis concerning the histograms and normal deviation curves. Since a high standard deviation indicates a spread of the data, this is interpreted by me that the conditions in the simulation were set up correctly. As stated in section 4.3, the random start time of the target entity will cause some iterations to have the platform and sensor and target entity at the worst angles for detection or identification. Additionally, some iterations might have more masking of the target entity behind buildings, causing reduced results based on the inability to detect or identify the target entity. As indicated by the standard deviation, this spread the results for each data set. Even with high performance metrics, the variability of buildings blocking the line of sight of the sensors resulted in lower performance numbers, regardless of the proficiency of the team. This forced FOCUS to constantly calculate probability of detection and identification as the target entity continuously moved behind buildings and the track was lost. Overall, this replicated a more realistic experiment in which environmental factors impacted the performance of the system and team to execute its task.

For the FMV data sets, the data follows the logic that due to higher performance potential within the High SA, there would be less standard deviation in the data set compared to the Medium and Low SA data sets. However, the similarity between Medium and Low SA in standard deviation indicate a more equitable distribution of the data set, with Medium SA earning higher overall results than Lower SA and thus performing better overall.

The opposite seems to be true for the IR SA data sets. Referencing Table 6 with the Acquire TTPM numbers, the closer Mean and Mode values and histogram analysis, supports the higher probabilities in initial calculation with IR sensors impacts the final results. Analysis indicates that the variation in SA (Low, Medium, High) has less of an impact on each data set if the probabilities for success are higher. Additionally, as supported by the results, the standard deviation is more equitable between the SA levels when utilizing an IR sensor and the variations within the simulation has a larger impact on the results than with the FMV sensor. These results support earlier research that attempts to improve the detection and identification capabilities of IR sensors to make them more equitable to FMV sensors (Lamdan and Wolfson 1988; Islam and Alam 2006; Deaver et al. 2009; Venkataraman et al. 2011; Wang et al. 2013; Gong et al. 2014b; Wu et al. 2015b). Unfortunately, due to the limited visual variations of IR output, the only success has been in merging IR and FMV sensor inputs (Dawoud et al. 2006; Teaney and Reynolds 2010; Eismann et al. 2010; Wu et al. 2015b).

5.2. Analysis of Baseline Results

The intent of the first hypothesis was to determine if the three levels of SA were significantly different. As already indicated through the histograms and descriptive statistics, each level of SA is numerically better than the lower level. With Low SA having the worst results and High SA with the best. To determine if the data sets are significantly different, an ANOVA was run with the results from the three SA levels. Table 11 is with the FMV results and Table 12 is the IR results.

Table 11 ANOVA on FMV results

ANOVA on FMV SA Data Sets

Source of Variation	SS	df	MS	F	P-value	F crit	
Between Groups	27994022	2	13997011	346	3.5E-124	4.62	**Reject null hypothesis**
Within Groups	60593680	1497	40477				**$F>F_{crit}$**
Total	88587702	1499					

Table 12 ANOVA on IR results

ANOVA on IR SA Data Sets

Source of Variation	SS	df	MS	F	P-value	F crit	
Between Groups	13742268	2	6871134	123	3.1364E-50	4.62	**Reject null hypothesis**
Within Groups	83542984	1497	55807				**$F>F_{crit}$**
Total	97285252	1499					

As indicated by the ANOVA results, and within each sensor data set, the three SA levels are significantly different from one another. Taking into account the descriptive statistics and histogram/normal distribution curves, the logical conclusion is that each level is also significantly better than the previous level. Medium SA is significantly better than Low and High SA is significantly better than both levels. The data supports this assumption for both sensors. Therefore, hypothesis #1 is supported by the results and the null hypothesis can be rejected.

5.3. Analysis of AiTR

After conducting 500 iterations for of the AiTR TTPM results, utilizing the values in Table 9, the correlation with the High SA level results was conducted between these two data sets for each sensor type. The correlation results for AiTR and FMV SA levels are in Table 13 and the AiTR and IR SA levels are in Table 14.

Table 14 Correlation between AiTR and FMV SA level

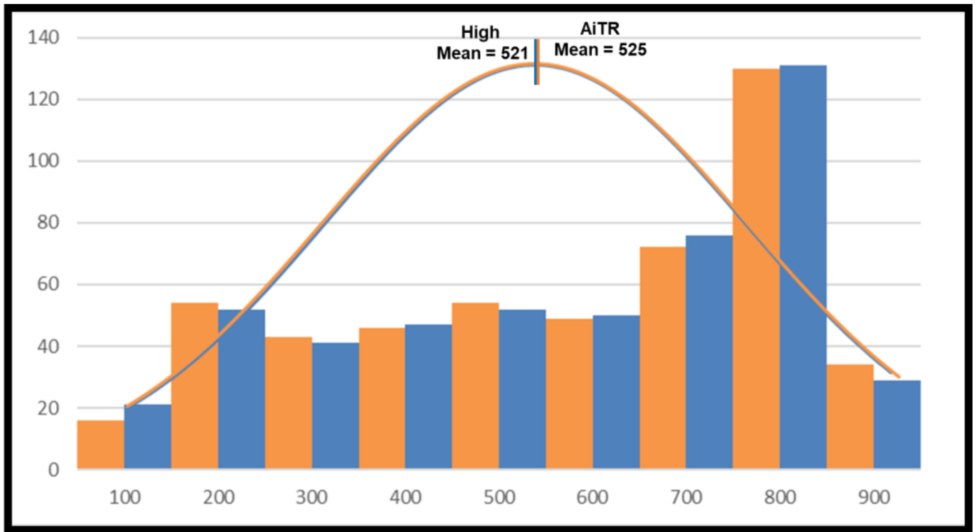
Correlation	High SA FMV	AiTR
High SA FMV	1	
AiTR	0.9999	1

Table 13 Correlation between AiTR and IR SA level

Correlation	High SA IR	AiTR
High SA IR	1	
AiTR	0.9999	1

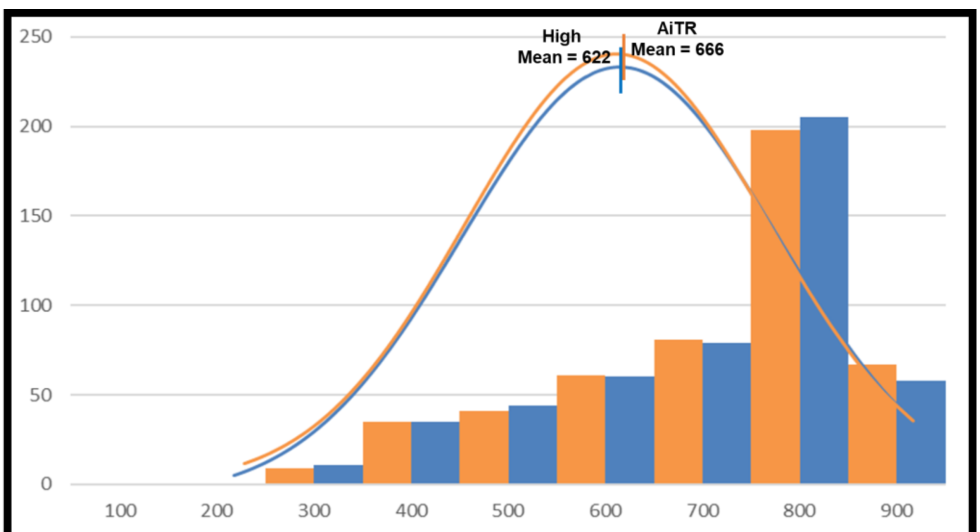
Both tables indicate a very high, almost perfect, positive correlation between the data sets. This indicates that the data is very similar and provides evidence that data collection between the data sets was normal, with not outliers or areas that need to be addressed prior to further analysis.

The next analysis step is to visualize the data through a stacked histogram with both data sets, overlaid with a normal distribution curve of the data sets to visualize how the data compares to one another. Figure 34 compares the IR SA data sets and Figure 35 compares the FMV SA data sets.



SA Level Results	AiTR	High SA
Frequency Histogram		
Normal Distribution Curve		

Figure 34 AiTR and High IR Data Set: Histogram and Normal Distribution Curve



SA Level Results	AiTR	High SA
Frequency Histogram		
Normal Distribution Curve		

Figure 35 AiTR and High FMV Data Set: Histogram and Normal Distribution Curve

Comparing the frequency of the histograms for IR (Figure 34), both AiTR and the High have a high level of similarity. The normal distribution curves are almost identical and the means have a difference of three. Histogram frequency distribution are almost identically left-skewed. Overall, the IR results between AiTR and High SA are very similar. This also is supported by the very high positive correlation between the two data sets. Analyzing the results for the FMV sensor (Figure 35) also follows the results for the IR sensor. Both have a high level of similarity in distribution and the means have a difference of only four. Initial results indicate almost identical data sets with AiTR only positive a slight better performance record.

Reviewing the descriptive statistics provides additional information on the analysis of the data. As indicated by the analysis on the histograms and normal distribution curves (figures 34 and 35), the descriptive statistics of mean and mode follow the same trends as shown in Table 15. With slightly numerically higher results for AiTR over High SA.

Table 15 Descriptive Statistics of AiTR and High SA Data Sets

Infrared Sensor				
High SA IR			***AiTR IR***	
Mean	**521.47**		Mean	**525.17**
Median	566		Median	569
Standard Deviation	**236.56**		Standard Deviation	**236.60**
Count	500		Count	500
Full Motion Video Sensor				
High SA FMV			***AiTR FMV***	
Mean	**622.36**		Mean	**666.53**
Median	712		Median	717
Standard Deviation	**155.20**		Standard Deviation	**155.02**
Count	500		Count	500

Given the analysis of the histograms and normal distribution curves, and the data in Table 15, both data sets of High SA and AiTR are very similar. Additionally, given the 0.9999 correlation between the data sets, this again provides evidence to the similarity of the two.

The intent of the second hypothesis was to determine if AiTR and the best performance SA level, which evidence determined was High SA level, were significantly different. As already indicated through the histograms and descriptive statistics, both of the data sets are very similar. To determine if they are significantly different, a F-test was conducted to determine if High SA and AiTR for both sensors had equal variance. Then a t-Test assuming equal variance was calculated to determine if the data suggests a significant difference or not. Results are shown in Table 16.

Table 16 F-test and t-Test results for High SA and AiTR

F-Test for IR - AiTR and High SA		
	High SA	AiTR
Mean	521.47	525.17
Variance	55958.44	55978.59
Observations	500	500
df	499	499
F	1.00	
P(F<=f) one-tail	0.50	
F Critical one-tail	0.81	

F-Test for FMV - AiTR and High SA		
	High SA	AiTR
Mean	662.36	666.53
Variance	24087.97	24030.22
Observations	500	500
df	499	499
F	1.00	
P(F<=f) one-tail	0.49	
F Critical one-tail	1.23	

t-Test: Equal Variance - IR		
	High SA	AiTR
Mean	521.47	525.17
Variance	55958.44	55978.59
Observations	500	500
Pooled Variance	55968.52	
Hypothesized Mean Difference	0	
df	998	
t Stat	-0.25	
P(T<=t) one-tail	0.40	
t Critical one-tail	2.33	
P(T<=t) two-tail	0.80	
t Critical two-tail	2.58	

t-Test: Equal Variance - FMV		
	High SA	AiTR
Mean	662.36	666.53
Variance	24087.97	24030.22
Observations	499	499
Pooled Variance	24059.09	
Hypothesized Mean Difference	0	
df	996	
t Stat	-0.42	
P(T<=t) one-tail	0.34	
t Critical one-tail	2.33	
P(T<=t) two-tail	0.67	
t Critical two-tail	2.58	

The F-test provided a high confidence of equal variance between High SA and AiTR for both sensor data sets. The F score (F=1.00) provides evidence of a very strong equal variance and similar data sets, this is also supported by the previous analysis in this section for these data sets. When the t-Test assuming equal variance was conducted, with a P >.01 confidence level, the results for the t statistic and P value indicate that the two data sets are not significantly different. Combined with the previous analysis, the null hypothesis is accepted.

However, the analysis supports the assumption that both data sets are significantly similar. This provides evidence that a team, augmented by AiTR technology, and with little or no training can perform at the same level as an experienced, trained team. In order to enable this assumption, each individual must be proficient in their own skill sets and those relevant to the task (Straus et al. 2019).

6. DISCUSSION OF RESULTS

Results from the experiments substantiates the hypothesis that the different levels of SA are significantly different and that each data set is notably better than lower versions. Even though the High SA data sets and AiTR were not significantly different, the evidence supports that they are considerably similar. Overall, the data collected in this work supports that higher levels of SA, supported by improved communications between team members, impacts the performance of a team at certain, specific tasks.

This contributes to the growing field of study of visual analytics by supporting the overarching goal of increasing understanding on the methods, technologies, and practices that exploit and combine the strengths of human and computer processing (Keim et al. 2008). A unique methodology of identifying a yellow taxicab, influenced by SA and GLU, was presented in this work. Its relationship with technology from aerial platforms and sensors to the images on a computer screen impacted the performance of a team of analysts in accomplishing their task. Improved AiTR technology also demonstrated a significant impact on the performance of this team, and how it can assist in ad hoc groups that are formed quickly in a disaster. Overall, this work examined the interactions aspects of this human – computer interaction.

Concerning the “Yellow Taxicab” problem, this research presents unique methodologies that can solve the problem quicker in a training setting. It provides additional evidence on how training, technology, and human interaction impacts the performance of a team to successfully complete the task. Additionally, it provides additional areas of potential study on how even better results might be produced.

6.1. Limitation of data sources

Since a simulation is a replication of a world of infinite variables, there is no way to completely imitate all of the possibilities a team or piece of equipment might encounter. Therefore, a simplification of the environment must be made to allow for proper computation and control of the experiment (Saunders and Beard 2010; Collett et al. 2013; Amaran et al. 2014; Nakano et al. 2016; Rybing et al. 2016). This creates a level of artificiality in the experiment that must be addressed and acknowledged. Even though a more realistic experiment would be ideal, the cost and complexity of conducting such an event is financially and computationally unfeasible; therefore, simulation are better utilized when better focused on performance measures and variables that can be isolated (Cannon-Bowers and Salas 2009; Saunders and Beard 2010).

For this work, an important decision was the removal of any weather from the simulation. This allowed the experiments to focus on the dependent and independent variables but removed a level of realism which could have impacted the results. Additionally, the performance values and the overall programs that executed all searches and platform movements was simplified from real-world tests. Even though they were based off of observed experiments, there is still a level of realism that is lost in these environments (Ratches et al. 2001; Vollmerhausen and Jacobs 2004; Vollmerhausen and Robinson 2007; Vollmerhausen 2009). A possible result from this replication is that the cognitive communication performance metrics perform better than they would have in an experiment with real equipment and subjects. Replicated communication equipment and lack of environmental factors would improve communication clarity and reliability (Artman and Garbis 1998; Cooke et al. 2005; McKendrick et al. 2014). Even though FOCUS hasn't been evaluated on this measure, it could have bias within the programming that places a higher value on communication and performance than has been evaluated or noticed in previous experiments. This could affect the outcomes of the different data sets during the experiment.

Concerning the performance values of the platform and sensors, these were also captured from previous evaluations and experiments; however, they have been validated and perform within the parameters established by the U.S. Army (Burghardt et al. 2015). Variations in these performance values could have an unknown impact on the simulations and the results. However, the large standard deviations, discussed in previous section, indicate that a level of realism was incorporated into the simulation with buildings blocking the line of sight between the target entity and the sensors. These results suggest that the simulation operated within expectations, with a constant re-acquisition sequences required.

Another area that requires additional evaluation is the use of the data from Ahmed et al.'s (2014) experiments on cognitive communication performance measures. Even though the experiments within this work closely matched those of that experiment, utilizing this model was the best fit for the simulation, there could be enough differences between the two experiments that the use of the data in the Bayesian Network conditional probability table (CPT) could create unvalidated results. This use would need to be further evaluated to ensure there is not unknown measured influence upon the results. Additionally, the work of Admed et al. (2014) isn't well referenced or widely used in other aspects of measuring cognitive performance.

Additionally, there are other communications variables that were not incorporated into the experiments. A limitation on bandwidth for the transportation of data and its impact on the ability to utilize high definition images was not addressed and incorporated. In real-world situations, this would impact the results since bandwidth is reduced due to changes in atmospheric conditions or other environmental or technological impacts (Porter et al. 2010; van Eekeren et al. 2015; van Huis et al. 2015). The assumption in this experiment is that sufficient bandwidth would be available to provide the necessary frame rate and fidelity for the analysts to do their job. This is relevant to this experiment since the TTP metric is based off of an analyst looking at a screen with high resolution images (Vollmerhausen and Jacobs 2004). Additionally, research also provides evidence that higher fidelity images created better results in detection and identification tasks (Alam 2006; Vollmerhausen 2009; Hsu-Yung Cheng et al. 2012; Cao et al. 2012; Maurer et al. 2013).

6.2. Implications and Synthesis of Results

Existing literature on communication indicates a strong correlation with training as a team and the quality of communications that occurs within or outside that team (Patrick et al. 2006; Cooke et al. 2013; Endsley 2015; Rybing et al. 2016; Sorensen and Stanton 2016). This could provide a way to express the level of communications, or overall, training of a specific team in an event that comprises many such teams. As indicated by existing research, a strong correlation between training and SA of a team exists and supports this interpretation (Patrick et al. 2006; Walker et al. 2008; Patrick and Morgan 2010; Seppänen et al. 2013; Sorensen and Stanton 2013). Therefore, the assumption is that the better trained team, with training on communications, will produce better results on specific tasks than less trained teams. The results from the first experiment support this assertion with the team possessing higher SA, which better cognitive communication performance metrics, earned more identifications in the 500 iterations than the other SA levels.

As supported by this experiment, the uncertainty in the geographical location of the target is also affected by the communication quality and both impact the level of SA for the team. Lower levels of communication performance increased the level of uncertainty due to miscommunication of the message. Several research articles have indicated that poor communication increases reaction time and impacts the performance of a team in completing a task due to more time allocated to finding a specific location (Artman and Garbis 1998; Nelson et al. 2004; Cooke et al. 2005; Bayrak and Grabowski 2006; Han et al. 2013; Sorensen and Stanton 2016). Results from the experiment executed in this work support these articles. Teams with lower SA levels, and worse communications, earned less identifications in the iterations of the experiments. The main reason for these performance levels is that their chance to re-acquire the targeted entity was worse and took more time to detect and identify. In a limited simulation, this would ensure that the teams that are unable to work efficiently as a team, with good communications, would produce worse results. Ultimately, this impacts the performance of tasks that require accurate location.

The results from hypothesis #2 and the incorporation of AiTR technology into the DSA model provides evidence of a potential solution when trained teams are not available to complete a mission. Since it takes time and resources to effectively train a team to complete a detection and identification task, this work provides support that this technology can enable a team to work at the same level as a trained team with high SA and communication skills. Importance of this research is when ad hoc teams are built at crisis areas like natural disaster sights or search and rescue operations. In order to maximize the human resource pool, individuals can be quickly integrated through AiTR technology and be able to operate at a much higher proficiency level. This research doesn't explain how these individuals could be integrated, but it provides evidence that investing in this technology will prove beneficial to increase team performances.

Overall, evidence was produced that expected results can be generated in the current configuration of the experiment and how FOCUS and the data is utilized/configured. Results support the assumption that SA, and its subcomponent of communications, impacts the effectiveness of identifying a target entity in a complex, urban environment. SA also has a relationship with GLU and this also impacts the ability of a team to accomplish this task and this GLU is perpetuated through the system as supported by the DSA model. Teams with higher SA perform better due to the minimization of GLU and miscommunication; however, this training required for higher SA can be mitigated by the use of AiTR technology.

7. SUMMARY AND CONCLUSION

7.1. Summary

As stated by, Johnson and Hanson (2011) the goal of visual analytics is to identify the best automated processes for the task at hand. Estimating limits that can't be further automated and then develop a tightly integrated solution that adequately integrates the top automated processes and human performance methods into a cohesive methodology. The goal of this research was to provide a framework that integrates unique aspects (geographical location uncertainty, human communication performance, human visual system, and mental constraints) within the parameters of the DSA model. Once integrated, this model would able to predict performance for the specific task of detecting and identifying a specific entity in a complex, urban environment.

Upon analysis, the results supported the assumption that variations in human communication performance (Message Quality (MQ)), based on the level of training and voice communications, impact the other variables of the model and nodes within the system and overall SA of the team. For the model, this includes GLU and the cognitive, mental abilities identified by Task Load (TL) and Working Memory (WM). Since training impacts the communication and SA of the team (Patrick and Morgan 2010; Seppänen et al. 2013; Sorensen and Stanton

2013, 2016), this work demonstrated a positive correlation between verbal communication proficiency and performance outcomes. With higher verbal communication skills, and higher SA, producing significantly better results than lower SA skill levels.

This work also demonstrates a potential solution to ad-hoc, or quickly formed teams needed to accomplish a detect and identify task in reference to an accurate location. For teams that are unable to train prior to the execution, this work proposes another solution utilizing the technology solutions with the Aided Target Recognition (AiTR) field. Experiments run utilizing AiTR indicated a removal, or significantly reduction, in the verbal communication (and subsequent GLU effects) which results comparable to those with high SA and higher levels of training.

7.2. Conclusion

This research postulated that the targeting and identification process presented in this paper, consisting of two different sensors, each with an independent human analyst, can be improved to better replicate a real-world environment. Concerning the “Yellow Taxicab Problem,” and actually identifying a yellow taxicab in a complex, urban environment, this research provides addition areas of study and alternative methods to solving this problem in a more efficient and effective manner. Not only must the analyst find the target, they must communicate its location to another analyst that had to identify it based on prior knowledge (i.e. type, color, etc.). Working together as a team, these two analysts utilized two specific sensors, FMV and WAMI, to detect and identify this targeted entity within a complex, urban environment. Buildings, targets, aerial platforms, and sensors were replicated within the simulation program, FOCUS, that incorporated authoritative data from its databases.

The basis for this research was to take the established TTP metric and to make it more responsive to team dynamics and other real-world variables. Incorporating the evolving research revolving around situational awareness (SA) brings into account the additional studies on the difference between ground truth and what people and their technology perceive or understand. This interaction between human beings and their technology is the basis for the theory on distributed situational awareness (DSA) model and the reason it was chosen for this work (Stanton et al., 2006; Salmon et al., 2008a, 2016; Neville and Salmon, 2015; Sorensen and Stanton, 2016). Within this model, SA is based on the interactions between agents (human or technological) within a collaborative system. Overall, a system's situational awareness, specified as the identifying the targeted entity in this work, is dependent upon the network and the communication of the information upon it. The TTP metric focuses on the internal mental processes of the human analyst on interpreting information that is presented on a computer monitor. However, when applying this outside of the DSA model the rest of the system and the communications resident in that process are neglected. Incorporating the human cognition performance metric by Ahmed et al (2014) models a portion of this system that deals with the quality if human communication, task load, and other cognitive loads that effect the ability of an analyst to complete a specific task. In this experiment, that task is ultimately the identification of the targeted vehicle of interest for this work.

In conclusion, this work provides a new metric to determine the probability of completing a task, identification in this case, that is impacted by the situational awareness of a team of humans and their supporting technological agents within the system. The TTP metric could be replaced by another metric that focuses on another task, but this work provides additional support to the DSA theory and the impact that technology, humans, and uncertainty have on SA. It also concludes that AiTR technology can have a large impact on assisting teams and their systems in completing specified tasks. Other intriguing avenues of research were discussed and possible assumptions that could be tested. Overall, this work is a study in science of the artificial; therefore, I would like to end this work with a quote from Herbet A. Simon from his book, <u>The Science of the Artificial</u>, commenting on the task of natural science.

> To show that the wonderful is not incomprehensible, to show how it can be comprehended but not to destroy wonder. For when we have explained the wonderful, unmasked the hidden pattern, a new wonder arises at how complexity was woven out of simplicity. The aesthetics of natural science and mathematics is at one with the aesthetics of music and painting both inhere in the discovery of a partially concealed pattern. (1996)

7.3. Future Work

Given the results of this work, the argument is made that the substantial positive results between the differences of other levels of SA are important in the use of AiTR technology. As other research indicates, there is a positive correlation between the level of training that a team undergoes and the level of performance of a specific task where communication, or SA in this case, is measured. Applied to this work, that would mean better training, thus higher SA level, will produce better task performance results and more identifications. Since training takes time and resources, another area to research is this relationship between training a team and the use of AiTR to off-set the cost of creating highly proficient teams. Additionally, a possible research questions would compare the differences in cost and resources to train a team and those that are trained on AiTR. Would those trained on AiTR create even better results?

Not only would training be affected, but the WM utilized in this experiment and from Ahmed's et al. (2014) research is a constant value. Another aspect that could be evaluated is how the WM of each analyst would change over time. WM would not remain constant as fatigue or other environmental effects would affect the behavior or capacity of the human analyst. This decrease in WM could bring "Information Overload" into the experiment, which would decrease the performance of the analyst and effect overall performance of the team.

Further research would also be beneficial in determining the optimal number of sensors for this specific task and terrain. Two sensors were utilized in this work, but would better results be calculated with three or more sensors? Could one sensor record appropriately sufficient results? This would be a cost benefit calculation for an operation, where the least number of sensors would save money while performing within an adequate band of success. An experiment could be set up to determine the ideal number of sensors for different situations or performance requirements.

Another area to discuss is the impact of bandwidth between the aerial platforms and the ground station when using AiTR. This was briefly discussed in this experiment; the bandwidth was a constant and did not change. In real-world situations, this would also hold true in the best situations, usually bandwidth is reduced due to changes in atmospheric conditions or other environmental or technological impacts (Porter et al. 2010; van Eekeren et al. 2015; van Huis et al. 2015). The assumption in this experiment is that sufficient bandwidth would be available to provide the necessary frame rate and fidelity for the analysts to do their job. This is relevant to this experiment since the TTP metric is based off of an analyst looking at a screen with high resolution images.

Since this relied upon a simulation, executing the experiments with additional environmental factors would provide additional research relevant to the topic of task performance and identification of a yellow taxicab. This would provide additional evidence on how weather impacts the performance of a team and how different levels of SA and training impact the results.

Since the work of Ahmed et al. (2014) might have impacted the results of this experiment, executing this experiment again with real, living human analysts could provide additional research on this topic. Variables could be further examined to include training levels, different forms of verbal and digital communications, and other factors that could potentially impact the performance of the task. Some of which are hidden in a simulated environment. This type of experiment would allow a better understanding of the impact of the message quality of communication and the training of the team. Different variables of communication and training could be further investigated to determine if other correlations can be calculated. One of these aspects is the impact of Shannon and Weaver's (1964) communication theory on how entropy of the message and its uncertainty effects the information produced.

Doing a live experiment would also assist in validating this model for future work. The main validation of this model utilized in this work is from the U.S. Army; however, the incorporation of Ahmed's et al. (2014) work might cancel this validation. Conducting a live experiment would provide the data and variables to determine if live results are significant to the results calculated with this model. Then a more in-depth validation of the model could be accomplished.

Another aspect that could be evaluated from a live experiment is to test the GLU of the model assessment. Ground truth could be measured at a specific time and the assessed location of the analysts and the different agents within the system could be measured forensically. This would provide a better measurement between ground truth and assessed location to determine if the GLU aspects of FOCUS are actual valid or need to be adjusted.

Possible research to explore would be the work of Wu et al. (2015a) on the Pseudo Real-time Exploitation of Sub-Area (PRESA) framework for processing WAMI frames in real-time. What makes their work unique is their decision to not process the full frame in real-time (all 360 degrees of a WAMI picture), but to instead to create sub-areas (or area of interest (AOI)) of the frame and then process these in real-time. This allocation of computing resources improves the processing rate for those AOIs only – bringing them to real-time while the rest of the frames remain at a slower proportion.

The last subject to discuss is the question of scale. This team model (detector and identifier) can incorporate more than one detector or data transfer person, but in order for it to scale it must end with a decision maker (identifier) that is executing a specific task that is dependent upon the previous nodes. This is supported by the DSA model as it sees each node (human or technological) as interlinked. At a more macro scale, each team could act as a separate node that produces a task result that is then used as a primer for another team. Uncertainty will be propagated through this system and the communications within the team or between team will also impact the SA of the overall system. This has been well researched in the DSA model (Walker et al. 2008; Seppänen et al. 2013; Sorensen and Stanton 2013; Endsley 2015; Dogan et al. 2011). However, increasing more complexity into this model will likely reduce its ability to successfully execute its task.

The results of this work provide other researchers evidence and the tools of how to incorporate more complex systems utilizing the DSA model. Further research could examine how SA and GLU impact the performance of a task, and to better understand the human-computer interaction that is growing more prevalent in a technologically improving society. This work provides alternative ways on how technology impacts human performance. As a starting point, this research provides additional evidence to those organizations in which location and time are an important aspects of accomplishing their mission, even those individuals looking for a yellow taxicab in an urban environment.

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