INTRODUCTION

Insurgents have effectively employed asymmetric tactics, such as the use of suicide bombers, as viable threats in urban environments. These threats are often devastating in their physical and emotional effects. They are hard to detect and have proven difficult to thwart or defeat. The U.S. Army has recognized that improvised Explosive Devices (IEDs) pose a persistent and devastating threat, impacting unit operations, U.S. policy and public perception (U.S. Army, 2005).

Suicide Vehicle-Born IEDs (SVBIEDs) would be easier to thwart or defeat if the political, cultural, and physical environments in which they were implemented were more readily constrainable as in full combat operations. However, in Stability, Security, Transition, and Reconstruction (SSTR) Operations, it is important to allow the nearly free flow of people (noncombatants) and goods through an economically developing or thriving community. The involved urban environments can be physically complex and culturally diverse. Threats that employ SVBIEDs take this into account and use this to their advantage. Our current, limited understanding of the human behaviors that drive the insurgent’s decisioning and responses, and the insurgent’s ability to capitalize on the nature of the urban environment in stability and support operations adds to the complexity and challenges of detecting and defeating this threat. There is a need to increase our understanding of the behavioral aspects, or responses to perceptions regarding the environment, of such threats so we can evoke responses that decrease their probabilities of mission success and increase our advantage in this contemporary operational environment.

The goal of the IDFW 15 effort was to determine the value of adding Unmanned Aerial Systems (UAS) to the aforementioned environment. Specifically, we looked to derive insights about semi-autonomous UAS with swarm behaviors.

This extension can assist counterinsurgent forces in several ways. It will drive needs for UAS allocation and development by identifying critical elements of semi-autonomous swarming behavior. In addition, it may highlight mission behavior that shows the most promise by expanding the tasks and environment beyond this current set. Due to the complex nature of the problem, the current state of understanding in the field, and the exploratory nature of the research, insights vice specific answers are central in this research.

PROBLEM STATEMENT

This study addresses whether we can isolate factors needed to identify effective semiautonomous UAS behaviors that add value to the aforementioned SVBIED TCP study. Ideal UAS implementation would maximize the area searched and minimize time between UAS passes within a defined geographic zone in order to locate and track SVBIEDs.

In the study scenarios, insurgents selected a fixed target, planned a route based on awareness of friendly TCPs, and moved through an urban environment to attack the target using one SVBIED. While executing the mission, the SVBIED could be detected by roving UAS or encounter TCPs of which they were not previously aware. If the SVBIED was identified by a UAS, selected TCPs within the local neighborhood would change from a static to a mobile posture. The mobile TCPs would receive updated SVBIED locations from the UAS in contact. They would then close with and interdict the SVBIED.

Within this context, we investigated the following study questions:

- Is SVBIED mission outcome a function of varied UAS swarming behaviors where mission outcome is SVBIED reaches primary target and detonates, detonates at an alternate target, or fails to detonate at any target?
- Does swarming behavior enhance UAS performance when searching an area for a specific target?
- In cases where the SVBIED reaches its primary target, what factors are important?
- In cases where the SVBIED detonates at alternate location, what factors are important?
METHOD

Team 4 used the Map Aware Non-uniform Automata (MANA) agent based simulation as it was also the simulation used for prior experiments with this study. MANA provided the flexibility we needed in agent personality, communications architecture, and agent behavior to effectively model employment of UAS in a variety of ways.

This research incorporated principles from several fields to explore factors associated with effectiveness of strategies in asymmetric environments. Agent based modeling, large-scale experimental design, and artificial electro-magnetic field theory were used to develop methods for capturing complex adaptive system behavior associated with nonlinear interactions. The artificial electro-magnetic field theory was used for global insurgent path planning and UAS separation. An agent based modeling environment was selected for implementing and executing the scenarios. The large-scale experimental design was used to establish factor settings (e.g., UAS speed, Swarm Behavior) for the scenarios.

Previous studies focused on exploring the impact of friendly and adversary capabilities and TCP strategies on SVBIED mission outcomes. These experiments ranged from a single target with a static defense array and sparse road network to multiple targets with a dynamic defense array within a dense road network. Capabilities examined included friendly and adversary communications and sensor performance during mission execution. The strong association of TCP strategy with SVBIED mission outcome spurred this extension of the investigation and led to the current set of experiments.

The visual representation of the current study appears similar to the previous experiments. Visually, it looks as though we’ve only added 3 UAS. However, there is a different command and control structures for the counterinsurgent forces. In addition, previously static TCPs can move to an SVBIED when it is identified.

The area of interest is a 5km x 5km box representing an urban area with a dense road network. The network consists of primary and secondary roads. There is an array of TCPs meant to interdict SVBIED attacks, background traffic, and a target. In addition, there are a number of spotters to provide information to the SVBIED and its escorts as it travels toward the target.

Our baseline simulation used UAS in the simulation with prescriptive programmed behavior to represent the present state of the art. In addition, they reported data to one central ground station. We assumed transmitted data would be in the form of video transmission and associated metadata such as time and geographic locations of both the UAS and its observations. We also assumed there was no direct communication between any of the 3 UAS.

We developed factors on interest based on insights gleaned from previous simulation attempts at swarming UAS. We employed a consistent TCP allocation to negate the influence of that factor. Within MANA, factors considered were the following: UAS Detection Range, UAS Classification Probability, UAS and TCP Communications Delay, UAS to UAS Repel tendency, UAS Inorganic Situational Awareness (ISA) Persistence, and UAS Speed.

Figure 1: Urban Environment with Dense Road Network

The factors UAS Detection Range and Speed are self-explanatory. Ideally we wanted to maximize both, but we realized significant increases in speed can result in a degradation of the UAS observation capability. In addition, we didn’t want to model unrealistic detection capabilities. Instead, we modeled a modest ability for the UAS to detect and classify a target as an SVBIED. Because this study may be used to drive future capability development, we thought this feature was important to explore.

UAS detection capability was modeled because we assumed that some intelligence about pending SVBIED missions existed. That intelligence, however strong, would be fed to the UAS and their operators. It would provide some guidance as to when or where to begin a search as well as what the SVBIED may look like. We think this is plausible. Even in areas where coalition forces are unable to affect the SVBIED decision cycle, forensic and historical data exists. This data could be used as a substitute for real time or actionable intelligence. A semi-autonomous UAS would use the information and an estimation of its veracity to drive its search pattern. A UAS ground station operator would essentially do the same thing with his reconnaissance plan.

The factors we manipulated to explore swarming with the MANA software were UAS Repel, and UAS ISA Persistence. These two factors seem to be keys in simulating swarming behavior. The essence of swarming behavior is an entity’s situational awareness (SA) as a function of the group’s situational awareness given current or recent input of other local entities as they collaborate on tasks. Updates to the global and individual SA elicit changes in behavior for each entity.

This self-organized behavior optimizes the group’s effort. For instance, ants, when searching for food, move along trails and leave a scent, a pheromone, to mark their presence. If other ants in the area come upon the trail and detect high levels of pheromone, they too begin to follow the trail. Low levels will cause them to ignore the trail. This is because high levels of pheromone indicate high traffic flow. The ants are programmed to assume that high traffic flow means success location of a close by food source. This

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strategy ensures that the colony exhausts any nearby food before other more arduous exploration begins.

In the simulation, the assigned collaborative task is identification of SVBIEDs within an urban setting. Here, swarming behavior ensures that the UAS are continually conducting surveillance throughout. As a strategy, UAS should remain dispersed so as not to overlap. Still, they need to revisit each other’s paths after time has passed for vigilant observation. Varying the UAS’ repellence between each other allowed us to set how far apart they would remain from each another.

If the inter-search time between observations is too long there may be gaps in the reconnaissance that would permit an SVBIED undetected travel to a TCP or its intended target. We addressed this with the ISA persistence. It varied the strength of the memory or the pheromone left when a UAS last passed over a location. Opposite from the ant example, UAS would be compelled to return to areas where the pheromone is weak.

Swarm behavior can be an optimization tool that balances simple jobs to meet the larger task of finding SVBIEDs. Varied levels of the factors as well as assigned UAS routes allowed for representation of 3 different types of swarming behavior as well as two variations of a baseline (no swarm) behavior, No Swarm A, No Swarm B, Daisy Chain, Central Hub, and All Net.

UAS in the No Swarm variants did not interact. They shared no information nor did they sense or repel each other. Daisy Chain, Central Hub, and All Net represented swarming of semi-autonomous UAS. Thus, the 3 UAS in each scenario used information from the others to self-organize within the reconnaissance zone and search for SVBIEDs.

UAS in No Swarm mode strictly followed preprogrammed search patterns to search the urban area. Swarming UAS were given general guidance by assigning paths but instructions also included generous levels of stochastic behavior. This allowed the UAS to stray from paths based on information from its UAS swarm-mates. Differences in the organization of the UAS defined their designation Daisy Chain, Central Hub, or All Net. Factor levels were varied for all UAS strategies in order to measure their influence on mission outcome as well.

EXPERIMENTAL DESIGN

To address the study questions, seven factors as shown in table 1 were incorporated into a nearly-orthogonal Latin hypercubes (NOLH) experimental design. A full factorial design would have yielded thousands of design points. Using NOLH, we reduced the number of design points to 17 and executed 25 replications per design point for a total of 425 runs. Each replication was a realization of a stochastic process of UAS behavior, route selection and traffic flow as modeled in MANA. This was done for each of the 5 UAS strategies.

Due to excessive run times for each simulation (over 96 hours), we have yet to analyze all of the output data. Our hope is that some, if not all, of the factors are significant and that the different UAS strategies yield statistically different outcomes in reference to the rate an SVBIED will detonate at its intended target.

INITIAL FINDINGS

Though we cannot offer any analytical bounty from this effort, there are a number of insights thus far. The first speaks to the length of time our simulation requires for 1 run. Each simulation can take up to 26000 steps (over 7 hours in real time). With over 2000 iterations to run, this is a labor intensive effort.

The runs are long for two reasons. The background urban traffic flow reaches steady state at about 8000 steps. For the model to be valid, this warm up period is a necessity. The
traffic congestion is indispensable in order to determine the strengths and weakness of strategies in an urban region. Realistic traffic throughput defines the current environment for all players.

In addition to reaching steady state, the stochastic nature of the SVBIED movement and probability of UAS or TCP success make end time estimations difficult to gauge. The long runtime is a reflection of our desire to capture as many final outcomes as possible. We will analyze the data associated with SVBIED interdiction or detonation to fine tune the simulation run times.

There were a couple challenges in the model as well. It was difficult to mimic the UAS ability to detect and classify a target as an SVBEID. We didn’t want the camouflage of the SVBIED so low that the UAS were not valued added but we didn’t want the UASs to be omnipotent either.

We compromised by linking the SVBIED escorts to the UAS. The escorts knew where the SVBIED was at all times. We arranged for at least one of the UAS to have contact with an escort and receive updates. To level the playing field some, we varied reliability of the escorts’ ISA as it was transmitted to the UAS. Then the UAS more or less knew the VBIED location and description. We felt this method mimicked the sparse intelligence units currently have about SVBIED operations.

Another challenge was modeling swarming in MANA. We were able to mimic pheromones and their fleeting nature by using the Persistence value parameter. However, we were unable to verify that we could fine tune a UAS’ receptors to react to pheromones. We had very little information about the ranges at which the pheromones were helping drive UAS behaviors.

**THE WAY AHEAD**

After collecting the forthcoming data, we hope to further explore important factors by recreating this experiment in different environments using different goals and tasks for the UAS. This would help us determine which UAS strategies are most effective in each environment. For example, in a civil search and rescue scenario, the Daisy Chain may be sufficient. However in a hostile situation, the redundancy of other methods may prove necessary. Tasks to be explored include various types of reconnaissance, direct fire engagements, search and rescue, and forward observation. Settings of interest include both conventional and unconventional conflict, natural disaster, and border patrols.

The intricacy and dire outcomes of the SVBIED problem demand high fidelity models to gain traction and begin validation of new counterinsurgent strategies. We are investigating the construction of a federation of simulation models to study this problem. Though no small effort on its own, we will try to mimic the success of federated training models. We will leverage models that best represent the sub-elements of this complex adaptive system. We hope to build a user friendly model that varies parameters within a constructive simulation and farming output data by leveraging the best tools available.