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Simulation analysis of UAV and ground teams for surveillance and interdiction

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Abstract

As unmanned aerial vehicles (UAVs) become more prevalent on the battlefield, ground forces will increasingly have to rely on them for intelligence, surveillance and reconnaissance, as well as target marking and overwatch operations. This paper presents the use of the Situational Awareness for Surveillance and Interdiction Operations simulation analysis tool in conjunction with the design and analysis of experiments to study aspects of UAVs' surveillance characteristics in conjunction with ground-based interdiction teams to aid in increasing the number of targets cleared from the area of interest. Different teaming strategies and coordination measures between searching and interdicting assets are studied in order to understand the effectiveness of the interdictor possessing an organic tracker UAV. The objective of this research is to quantify the benefit or penalty of an additional UAV asset that is organic to a quick reaction force in the context of the overall surveillance and interdiction operation.

Keywords

interdiction, experimental design, manned-unmanned teaming, unmanned aerial vehicles

1. Introduction

The Marine Corps has pursued developments with unmanned aerial vehicles (UAVs) to increase the force-multiplying capabilities that these enhanced, multispectral (electro-optical/infrared and synthetic aperture radar) systems bring to the fight to support goals aligned with the Marine Corps Vision and Strategy 2025.[1] Newly emergent concepts for unmanned aerial systems (UASs) employment will continue to enhance and extend the lethal and nonlethal capabilities of the Marine Air Ground Task Force (MAGTF). Joint Force Commanders will attain new levels of battlespace command and control and situational awareness by applying these newly emergent concepts. The UASs can provide the MAGTF with dedicated operational capabilities focused on battlespace awareness and force application while enabling enhanced command and control throughout the range of diverse military operations. In order to accomplish this, the Marine Corps will need to acquire significant numbers of smaller UAVs that will be organic to the ground combat element's table of equipment.

The Navy is concurrently advancing future applications of UAVs, as highlighted by the Chief of Naval Operations' (CNO) recent Strategic Studies Group (SSG) XXVIII study on autonomous systems, entitled "The Unmanned Imperative". Specifically, the SSG was tasked with showing how unmanned and manned systems interact and to optimize the command and control structure the better to integrate unmanned naval assets with manned systems. The SSG believes this integration will allow the Naval services to overcome the challenges of the 21st century. In order to accomplish this, UAVs need to become more capable. One of the critical capabilities of the UAV is autonomy, where autonomous systems can be thought of as possessing different "levels of autonomy" with some degree of human interaction combined with machine automation. Future concepts

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of operations (CONOPS) for all services will increasingly rely on this capability in some form, as many current UAVs, such as the Global Hawk, already operate with some degree of autonomy. A high level of automation will be required for future concepts that include large numbers of UAVs. In many large-scale operations where high numbers of UAVs may operate, the ability to self-coordinate may be needed due to the increased difficulty for operators to control multiple teams of UAVs.

However, there is a pitfall if the number of UAVs and their uses are increased without viewing them as part of an overall distributed force. Many unseen and unexploited opportunities for the use of these systems may be missed. Thus, it is important that these systems be utilized in such a way as to maximize the integration of unmanned and manned systems. Studying the integration and future employment options among UAVs and the interdiction teams they are tasked to support is just a first step in this process. If ground interdiction teams are augmented with an organic tracking capability (the ability to track targets on their own) in the form of a man-portable UAV, the potential exists to more rapidly acquire and track a target, which would allow the surveyor UAV to be released from tracking and return to its primary mission of intelligence, surveillance, and reconnaissance (ISR) and target acquisition. It is believed the natural result of this interaction would be an increase in the number of targets acquired and cleared during interdiction missions.

This paper presents the development and analysis of a simulation model that is used to study manned–unmanned teaming (MUT) interactions with a quick reaction force (QRF) or interdiction team, to aid in the development of a CONOPS for UAV employment. The Situational Awareness for Surveillance and Interdiction Operations (SASIO) software is a simulation with a graphical user interface (GUI) that can be used to simulate real-time intelligence and aid in the development of strategic, operational, and tactical analysis that supports unmanned systems planning for specific theater scenario evaluation.

The SASIO software provides an analysis tool and is designed to study mission characteristics and performance involving surveillance assets, such as UAVs, in conjunction with interdiction assets, such as ground-based QRF teams. We examine different teaming strategies and coordination measures between searching and interdicting assets in order to study the effectiveness of the interdictor possessing an organic tracker UAV. The team's effectiveness is measured by the percentage of successful interdictions, i.e. detection, interception, and clearance, of targets of interest.

In many current operations, there is only a one-way flow of information, in that a ground unit may request an airborne asset to assist with its mission, but they do not have direct control over that asset. There exists a need within all services for new or better tactics and CONOPS for effectively teaming these ground units with organic UAVs. The objective of this research is to quantify the benefit or penalty of an additional UAV asset in the context of the overall surveillance and interdiction operation using the SASIO modeling framework. This objective is guided by the following research questions: is it better for an interdiction team to possess an organic ''augmented tracking'' capability in the context of the number of targets cleared, and what are the significant factors that produce teaming strategies that result in the greatest number of hostile targets cleared? In Section 2, we present a review of the relevant literature. This is followed by Section 3 describing the SASIO model and the theater scenario analyzed in this paper. The experimental design and analysis modeling techniques used to study the theater scenario and model results are presented in Sections 4 and 5, respectively. Finally, conclusions and future work are presented in Section 6.

2. Literature review

As UAVs become integrated on the battlefield, it is increasingly important to operate them in a highly efficient manner. This means improving the functional capabilities of UAVs. Three important areas for improvement as described in the Department of Defense's recent *Unmanned Systems Integrated Roadmap*[2] include: efficient routing of UAVs in the area of operations (AO), improved sensing or target acquisition, and better UAV teaming strategies. There has been substantial work published in the literature that addresses each of these three areas for improvement. A brief overview of these topics follow.

Efficient routing needs to take into account terrain, mission, search pattern, number of targets, and the network structure of the AO. This concept has been studied in McCadden,[3] where the author developed a decision support tool utilizing a dynamic program that provides efficient search routes for multiple UAVs searching for multiple targets on a known graph of nodes and arcs. This problem was extended to the study of path planning for multiple UAVs.[4] In this study, the authors addressed the problem of generating feasible routes for multiple UAVs in a target-rich environment. An anytime algorithm was developed using particle swarm optimization that results in routes whose quality increases with an increase in the computation time.

Two significant factors that affect sensing are the probability that a target exists at a given location and the probability of the UAV seeing and identifying a target. One can use the number of hostile targets identified as a measure of effectiveness (MOE) for a given employment strategy. Jin et al.[5] investigated the value of predictive target assignment as a function of the number of unknown targets and number of UAVs. Target neutralization time (i.e. the time needed to neutralize targets) and total mission time (i.e. the time needed to destroy all targets) were the MOEs used. The authors found that utilizing a prediction algorithm for target locations helped the cooperative UAV teams locate targets. As targets were located, they were stored in a database used by the UAV team to update target knowledge and thus update the prediction algorithm. As the target database increased, the predictions improved. In this study, the nominal density of targets within the AO is assumed to be known a priori and we utilize different search algorithms as factors for our MOE. Flint et al.[6] studied the value of utilizing probabilistic information about reports of object detections and incorporated this information into a database that includes probabilities of an object's existence as well as probabilities of its location. This aids in the discrimination of false and real objects.

Previous works have also explored various CONOPS for MUT, including work done by Kress et al.,[7] which takes advantage of a UAV's ability to detect targets and a ground team's ability to interdict those targets. In this work, an integer linear program was developed to optimize the employment and deployment of UAVs integrated with Special Forces. The goal of this model was to assist commanders in determining suitable locations for mobile control centers and ground control units as well as optimizing the search areas for the UAVs. The model resulted in 50% more target detections than manual plans generated by experienced commanders.

In order for success on the battlefield, UASs cannot be limited to operate in isolation. There must exist a level of coordination and integration with ground units. This problem was studied in an attempt to quantify the benefit of small, hand-launched UAVs as border patrol agents attempted to classify and capture illegal aliens at border-crossing sites.[8] The MOEs used for this study were the number of illegal immigrants classified and cleared and the number of smugglers classified and captured. This simulation-based study found there was an increase in correct classifications and clearances with the aid of these UAVs.

Utilizing similar methodologies as the works above, we determine the benefit or penalty to interdiction efforts by the addition of an organic UAV capability for a single interdiction team when used in conjunction with a surveyor UAV. We measure the number of targets cleared for a given AO size and target set. Target locations are not known a priori and we do not utilize a predictive algorithm for target locations. Specifically, we use the number of targets cleared as our measure of effectiveness. These results then have the potential to affect future CONOPS for the integration of UAVs with ground combat elements. Results of our simulation contribute to the development of a decision support tool that can aid the commander as he determines which targets to interdict based on which presents the highest priority.

3. SASIO modeling

SASIO is an agent-based simulation model written in the Java programming language. Agent-based modeling is used to study the interactions of autonomous agents in complex systems. Monte Carlo techniques are used to introduce randomness to the model. SASIO defines both agent and object modeling. "Agents" refer to friendly forces and "objects" refer to either neutral or hostile targets. SASIO is used to define and construct, for example, multiple search methods for agents, agent planning and interdiction behaviors, object motion models, and their respective interactions with the environment. SASIO was developed initially by Chung to provide a decision support system with application to broad area maritime surveillance and interdiction models described by Chung et al.[9] Byers[10] extended the SASIO model to investigate the use of an aerial surveillance asset in support of a tactical installation protection mission against vehicle-borne improvised explosive device attacks. This examination highlighted the benefit of earlier detections of threats by the UAV as well as the need to mitigate the target's speed by alternate measures. The SASIO modeling capability was also extended for the work described in this paper. A more detailed description of the SASIO model used for this research is found in Muratore.[11] The SASIO simulation software is flexible and allows the user to define the theater and scenario (UAS asset deployment). In the remainder of this section, the theater and scenarios used for the purpose of this research are described.

3.1 Theater description

The theater for this paper consists of a range of areas of operations from 10×10 km to 100×100 km. Each AO consists of 1 km $\times$ 1 km grid squares and represents any location where real-world operations are currently ongoing. The choice for this size grid square is consistent with the standard unit of measure for charts, maps, and gridded reference graphics used by ground and air assets in the current theaters of operation. The AO in this work can be thought of as abstractions or extensions of operationally relevant locales or of field experimentation venues where the insights from this study may be applied.

In the theater used for this research, QRF teams are located at a forward operating base (FOB) with the mission of interdicting and capturing hostile targets. Vehicle-mounted QRFs are nominally restricted to the existing road networks, whereas foot-mobile QRFs are less constrained to remaining on the road networks. The QRF is assumed to be able to travel either by foot or vehicle (e.g. HMMWV) to the target location when cued. Otherwise, the QRF is assumed to remain at the FOB until it receives a mission. Airborne assets in the simulated scenarios include a surveyor UAV that perform ISR within the AO. This UAV utilizes one of three specified search patterns to determine which provides the most target detections. Missions are generated from reports sent to the FOB by the surveyor. After the report is generated, the surveyor must perform one of two missions. First, it can continue to search for additional targets. Alternatively, it can transition to a tracking mode, updating target action and location in the form of additional reports to the QRF. Once the QRF arrives at the target location, the surveyor is released back to its search mission. The QRF has the ability to have a tracker UAV assigned to it as an organic asset. Launched by the QRF when the surveyor issues a report, the tracker proceeds to the last known target location. If the surveyor is tracking, it conducts a target handoff with the tracker. Once the tracker has positively identified the target, the surveyor is released to its search mission.

3.2 Scenario description

The scenario describes the number, movement, and prediction models of the red forces, known as ''objects''. Objects in this research represent targets or neutrals. We use experimental design as the basis for determining the significant factors for the presented SASIO simulation model. Experimental design allows for estimating the effects of the input variables simultaneously where variation of the factors is present. Screening experiments allow the experimenter to vary factors in such a way that the most significant factors can be identified with respect to the response variables of interest, with as little experimental effort as possible. The SASIO software encapsulating the model is designed to utilize design of experiments (DOE) to study the aspects of UAVs' surveillance characteristics in conjunction with ground-based interdiction teams with the overall goal of increasing the number of targets cleared. The model created for this research has one primary response variable of interest. The primary response variable is the percentage of targets cleared. This is the metric by which we measure the benefit or penalty of the different teaming strategies.

4. Experimental design and analysis development

The SASIO model is used to simulate the unpredictability of all entities in the AO and thus provides insights that demonstrate which of these factors have a significant effect on the response variable: the percentage of targets cleared. The percentage of targets cleared is an important metric that commanders wish to know: it relates directly to how efficiently assets perform for a given teaming strategy. The higher this number, the more successful the teaming strategy. Insights can be gained on which QRF mobility type is preferred and if it is worth the effort to launch the tracker based on the QRF distance to the target. This response is obtained directly from the interdictor cleared list stored within the SASIO output.

The factors to be investigated in this research are listed in Table 1. Each factor has an associate level, type and description which is also presented in Table 1. Each factor represents a characteristic of the entities in the simulation and the level represents a particular value the factor can take during the course of the mission. The team type is the

Table 1. The factors varied in the experiment and their associated levels.

Factor	Levels	Type	Description
Team Type	Surveyor Surveyor/Tracking Surveyor with Tracker	Categorical	UAV capabilities that are available to the QRF
Search Pattern	Random Walk Lawnmower Spiral	Categorical	patterns to be flown by Surveyor UAV only
Tracker Launch	[1, 3, 5]	Continuous	# cells from goal location
Interdictor Transit Time	[15, 2, 1]	Continuous	# time steps to traverse 1 cell
Tracker Speed	[1, 3]	Continuous	# cells traversed / time step
Surveyor Gamma (γ)	[0, 0.9]	Continuous	Constraint
Surveyor Rho (ρ)	[0, 0.9]	Continuous	$\gamma + \rho \leq 0.9$
Search Area	[100, 2500, 10000]	Continuous	# cells, C in the AO
Interdictor Clear Time	[1, 11, 21]	Continuous	# time steps
Number of Objects	[30, 75, 120]	Categorical	1:2 target to neutral ratio
Object Motion	Slow Random Walk Fast Random Walk	Continuous Continuous	Dependent on self transition probabilities, $\pi_{i,i}$

main focus of this study. Team type is the ultimate decision a commander will need to make in order to achieve his objectives. The first strategy utilizes a surveyor UAV only with no tracking capability. The second strategy represents a surveyor UAV that has tracking capabilities. The third strategy utilizes the surveyor but it is augmented with an additional tracking UAV, organic to the QRF. This factor can take on three discrete levels and is therefore categorical. Further details of the remaining factors are described in Muratore.[11] Note that for the analysis, the continuous factors are transformed to a scale of -1 to 1 so that they are unitless and can all be directly compared. For example, the factor tracker launch is converted to a scale of -1 to 1, so that its low level (-1) represents the value of 1 and high level ($+1$) represents the value of 5.

4.1 Optimal design

The choice of experimental design is developed to accommodate 11 input factors. The experimental design defines the factor settings used for each simulated scenario. The experiment developed in this research constitutes a mixed-level design, for which the design matrix is created using the *D*-optimality criterion that results in an orthogonal or nearly orthogonal design. For a detailed description of the *D*-optimal design, orthogonality and its role in design, and other experimental design choices, please refer to Montgomery.[12]

Factor screening is the process of systematically varying input factors in order to identify the factors that produce a significant change in the response variable. The screening experiment is used to estimate the magnitude and direction of individual factor effects as well as factor interaction effects on the response variable. A *D*-optimal design is used for the screening experiment in an attempt to minimize the variance of the model regression coefficients. The *D*-optimal design minimizes the volume of the joint confidence region on the vector of regression coefficients, which equates to minimizing the uncertainty of the regression coefficients.[12]

Traditional screening experiments are conducted using only two levels of the factors, a low level and a high level. Center points are added to the design to check for nonlinearity within the model and to reduce the variance in the center of the design space. The experimental design points are generated using the software package JMP 8.0.1.[13] The full design consist of 102 design points including six center points.

4.2 Logistic regression analysis

Multivariate linear regression can be used to determine which factors in the screening experiment have a significant effect on the response. In a linear regression model the response variable, y, is related to predictor variables, x_i: (for example the variables listed in Table 2), through the following relationship

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{1,2} x_1 x_2 + \cdots + \beta_n x_n + \varepsilon$$

Logistic regression is used for the prediction of the probability of the occurrence of an event. The event we are interested in is the probability of a target being cleared. The number of targets cleared is a Bernoulli random variable that can take the values of zero or one. Either the target is cleared or it is not. When a response variable is binary, the resulting shape of the response function is nonlinear.[14] This nonlinear function takes the form

$$\text{logit} = \frac{1}{1 + \exp(-\boldsymbol{x}'\beta)}$$

An examination of this function shows that it is easily linearized by using the logit transformation defined below as $\eta = \ln((P(x_i)/(1 - P(x_i)))$, where η is the linear predictor of the response variable y. By employing this transformation we are able to linearize the response variable and perform standard multivariate linear regression. For further reading on general linear models and the logit transformation, please see Myers et al.[15]

In order to convert the response variable to a percentage metric each experiment is replicated 60 times. The mean number of targets is determined for each unique experiment and then divided by the number of targets to attain the percentage of targets cleared. The resulting percentage is transformed via the logit function

$$\text{logit(percentage targets cleared)} = \ln\left(\frac{\text{percentage targets cleared}}{1 - \text{percentage targets cleared}}\right) = \boldsymbol{x}\beta + \varepsilon$$

This ensures that the response is on the $-\infty$ to $+\infty$ scale and multivariate linear regression is then appropriate. The replication number of 60 was deemed appropriate because this is the number of replications at which the asymptotic standard deviation stabilized amongst a number of test runs.

Tabel 2. The team type, Surveyor with Tracker, along with the combination of Tracker Launch and Tracker Speed. This team type is now listed as Surveyor with Tracker A–E.

Team Type	Tracker Launch	Tracker Speed
Surveyor with Tracker A	5	3
Surveyor with Tracker B	1	1
Surveyor with Tracker C	5	3
Surveyor with Tracker D	1	1
Surveyor with Tracker E	3	2

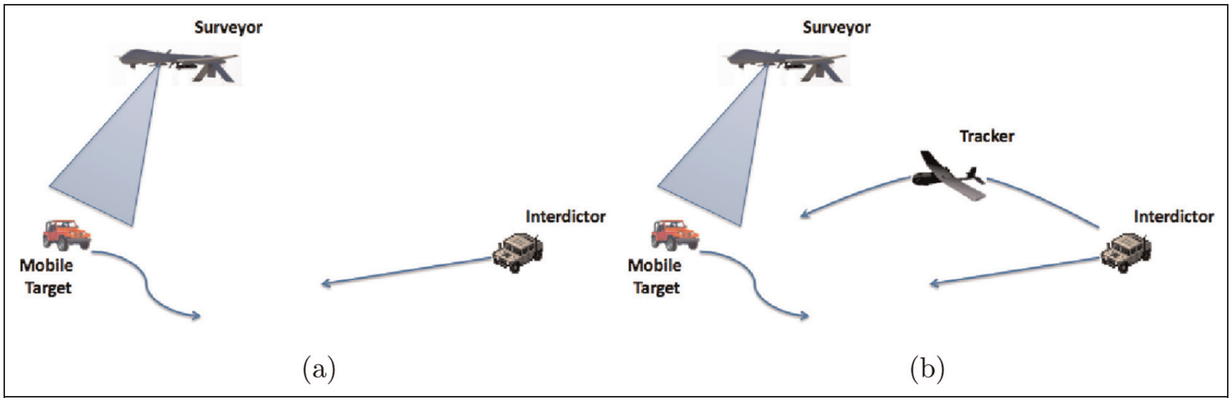
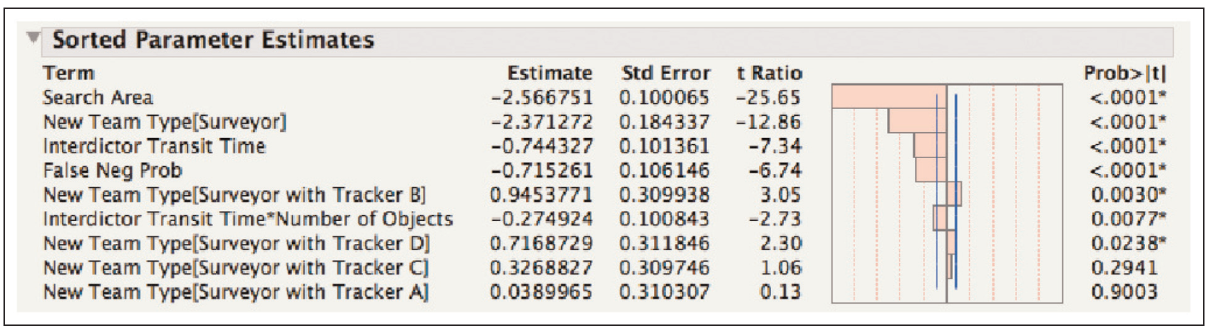


Figure 1. Graphical representation of the different concepts of operations employing different team types for surveillance and interdiction missions: (a) Surveyor and Surveyor/Tracking; (b) Surveyor with Tracker.



Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Search Area	-2.566751	0.100065	-25.65	<.0001*
New Team Type[Surveyor]	-2.371272	0.184337	-12.86	<.0001*
Interdictor Transit Time	-0.744327	0.101361	-7.34	<.0001*
False Neg Prob	-0.715261	0.106146	-6.74	<.0001*
New Team Type[Surveyor with Tracker B]	0.9453771	0.309938	3.05	0.0030*
Interdictor Transit Time*Number of Objects	-0.274924	0.100843	-2.73	0.0077*
New Team Type[Surveyor with Tracker D]	0.7168729	0.311846	2.30	0.0238*
New Team Type[Surveyor with Tracker C]	0.3268827	0.309746	1.06	0.2941
New Team Type[Surveyor with Tracker A]	0.0389965	0.310307	0.13	0.9003

Figure 2. Sorted parameter estimates of logit transformation of percentage targets cleared in order of significance. For example, the term search area has a parameter estimate of −2.57, which is the fitted value for the regression coefficient (beta) as shown in the equation in Section 4.2.

5. Model analysis and results

The first part of the analysis performed is to determine the effect of tracker launch and tracker speed only for the one team type: the team consisting of Surveyor with Tracker. To accomplish this, we ran five separate tests, which are illustrated in Table 2. Each combination is labeled A, B, C, D, or E and represents the Surveyor with Tracker team in conjunction with high–low combinations and center points of the levels of the tracker launch and tracker speed factors. This is done because these effects are not present for the Surveyor only and Surveyor/Tracking team types. For example, the team type of Surveyor only (see Table 1) does not have an associated tracker launch or tracker speed because there is no tracker available.

The analysis is now performed omitting tracker launch and tracker speed. Performing the analysis in this way allowed for the effects of tracker launch and tracker speed to be preserved for Surveyor with Tracker while at the same time being removed from the analysis in order to ensure those factors do not impact the team types where the tracker is not part of the simulation model. The remainder of this section discusses the results of the screening experiments and a sensitivity analysis performed as a follow-up.

5.1 Experiment results

The regression analysis consisting of only five effects is found to be a good model: R^2 and R^2 adjusted of 0.915 and 0.906 respectively, is achieved. Figure 2 lists the parameter estimates. Note that the factor 'new team type' is significant as a whole, though not every pairwise comparison of the categories within that factor are significant. This is why the last two variables listed in the table have high p-values.

The regressor with the largest coefficient is search area. As the search area is increased, a negative response in the percentage of targets cleared is anticipated. Our analysis is conducted using coded variables (i.e. a unitless scale

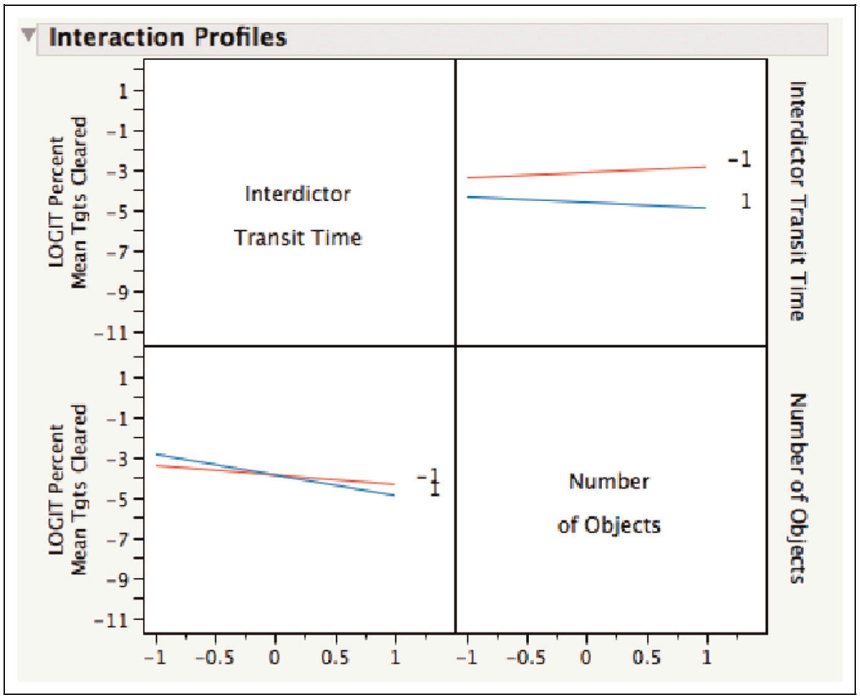


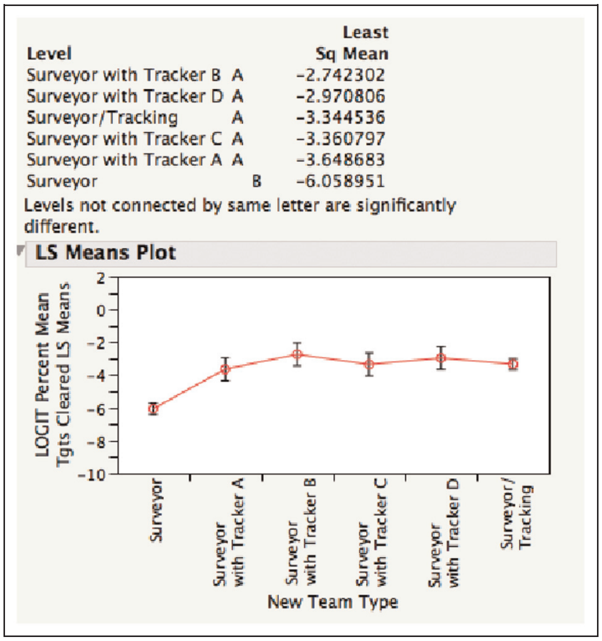
Figure 3. Interaction profile showing the change in response as search area size interacts with new team type. This plot shows that the mean targets cleared increases as the number of objects increases when the interdictor transit time is fast, and the mean targets cleared decreases as number of objects increases when the interdictor transit time is slow. The dimensionless horizontal axis corresponds to the use of coded units for factor levels.

between -1 and $+1$). The odds ratio for a single unit increase in search area is to be $e^{-2.56} = 0.077$, not taking into account the effects of the other factors. This odds ratio can be interpreted as the estimated increase or decrease in the percentage of targets cleared[14] per unit increase on search area. Therefore as search area increases from its mid-level to high level, the odds of success are approximately 8 out of 100. This model also shows that utilizing a team type comprising only a surveyor asset with no tracking capability produces the least desirable results in terms of the response. The corresponding odds ratio is $e^{-2.37} = 0.09$, which equates to a reduction in the odds of success to 9 out of 100. A similar argument can be made for interdictor transit time and false negative probability of detection.

The interaction (the sixth parameter listed in the output of Figure 2) of interdictor transit time and number of objects is worth examining. See Figure 3: as the number of objects increases, increasing the interdictor transit time still does slightly improve the percentage of targets cleared, while decreasing the interdictor transit time, as the number of objects increases, reduces the percentage of targets cleared. The QRF is simply overwhelmed by the number of objects to interdict. This result supports the argument for more QRFs or patrols if a target-rich environment is anticipated.

Tukey's least squares means differences allows us to perform a multiple comparison of the means to determine if there is a significant difference among any pair of factors. Tukey's method then groups the mean responses that are not statistically different as seen in the crossletter report (Figure 4). Also shown is a plot showing the difference in the means between team types with a tracking capability and those without. We can see a significantly lower mean response for Surveyor when compared with Surveyor/Tracking and Surveyor with Tracker. This supports our conclusion that possessing a tracking capability will positively impact the response. Though perhaps intuitive, the above analysis provides a quantifiable measure of the impact and operational value of such a capability, which can be used by decision makers in deployment and employment planning.

After establishing that possessing a tracking capability is better than no tracking capability, we are interested in the significant effects when the Surveyor team type is not included in the model. For this focused analysis, all surveyor data is removed. Stepwise regression produces a good fit with seven main and interaction effects. This model has R^2 and R^2 adjusted of 0.913 and 0.901 respectively. Figure 5 lists the significant factors from most to least influential for this model. Search area has the greatest



Level		Least Sq Mean
Surveyor with Tracker B	A	-2.742302
Surveyor with Tracker D	A	-2.970806
Surveyor/Tracking	A	-3.344536
Surveyor with Tracker C	A	-3.360797
Surveyor with Tracker A	A	-3.648683
Surveyor	B	-6.058951

Levels not connected by same letter are significantly different.

Figure 4. Tukey's crossletter report and plot of the least squares means showing new team type grouped by similar means. This shows that the surveyor with tracking capability or any tracker combination produces an equivalently high mean percentage of targets cleared. The Surveyor only results in a statistically significantly lower percentage of targets cleared compared with any other teaming combination with the exception of the Surveyor with Tracker at the lowest level of launch and speed.

effect on the response. The odds ratio is $e^{-2.29} = 0.10$, which equates to a reduction in the odds of success to 10 out of 100 per unit increase of search area, which is very close to that of the model with team type Surveyor included.

Interdictor transit time is the next factor in the list. Its inclusion is an anticipated result as is the effect of the surveyor's sensor characteristics. Increasing the false negative probability, ρ, reduces the percentage of targets cleared due to the increase in targets being misclassified as neutrals. An increase in the Number of Objects, coupled with other factors, increases the response simply because as the number of objects increases so does the number of targets.

Of greater interest is the lack of any effect from either tracker launch or tracker speed. In neither model do these factors have an effect. Tracker capabilities were modeled using the Raven UAV, the USMC's Group I UAV. Further study is required to determine if a tracker with greater capabilities would have a greater effect on the response variable.

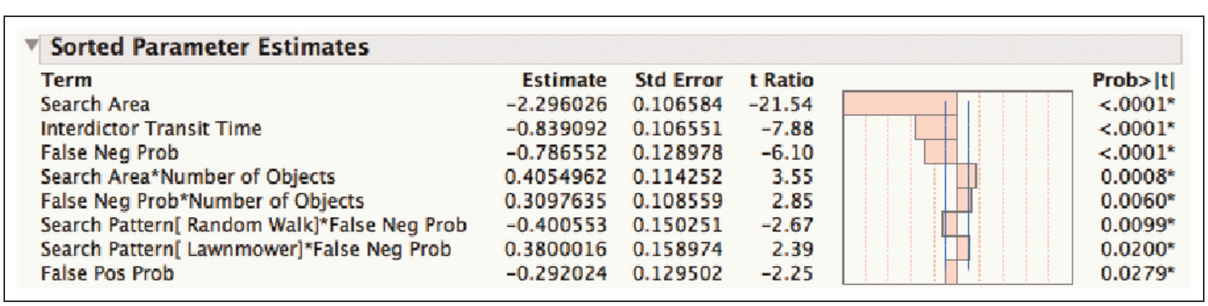
Table 3. Factor Levels used for Sensitivity Analysis.

Search Pattern	Lawnmower
Tracker Launch	3
Interdictor Transit Time	1
Tracker Speed	3
False Positive Probability	0.3
False Negative Probability	0.3
Clear Time	20
Number of Objects	120
Object Motion	SlowRW

5.2 Sensitivity analysis

Having determined that search area and team type have the largest effect on both response variables, we perform an additional analysis to quantify those effects. All factors are held constant with the exception of team type and search area. The factor values used are shown in Table 3.

Team type is varied across three categories (Surveyor, Surveyor with Tracker, and Surveyor/Tracking) and search area is varied across six levels, resulting in 18 additional experimental design points. These points are replicated and the percentage of targets cleared is collected and presented graphically in Figure 6. This figure indicates that having a tracking capability is better than no tracking



Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Search Area	-2.296026	0.106584	-21.54	<.0001*
Interdictor Transit Time	-0.839092	0.106551	-7.88	<.0001*
False Neg Prob	-0.786552	0.128978	-6.10	<.0001*
Search Area*Number of Objects	0.4054962	0.114252	3.55	0.0008*
False Neg Prob*Number of Objects	0.3097635	0.108559	2.85	0.0060*
Search Pattern[Random Walk]*False Neg Prob	-0.400553	0.150251	-2.67	0.0099*
Search Pattern[Lawnmower]*False Neg Prob	0.3800016	0.158974	2.39	0.0200*
False Pos Prob	-0.292024	0.129502	-2.25	0.0279*

Figure 5. Sorted parameter estimates of logit transformation of percentage targets cleared in order of significance.

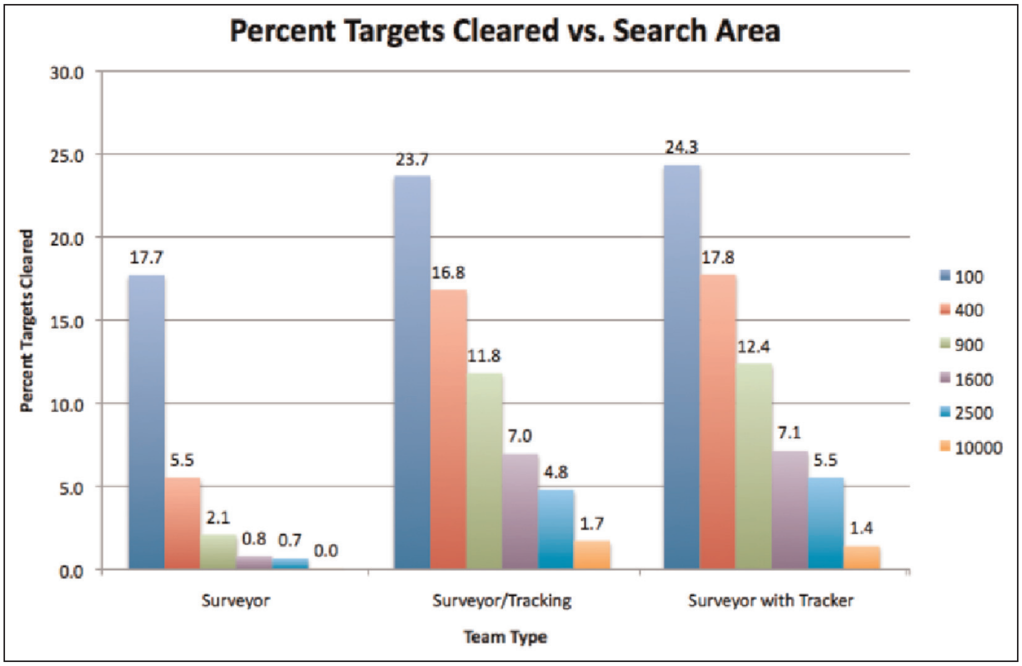


Figure 6. Average percentage targets cleared versus search area size.

capability. Holding all factors fixed with the exception of search area and team type indicates that as the search area is increased the percentage of targets cleared decreases. The significance of this analysis is to provide guidance on the minimum number of teams necessary within a given AO to achieve a desired level of mission performance. In other words, if the success of the mission is defined by the percentage of targets cleared, the presented model can identify deficiencies or excesses in allocated resources in order to conduct the operations effectively.

6. Conclusions and future work

The experimental results indicate that the factors with the greatest effect on a manned–unmanned team operation for interdiction are the team type and search area. Surveyor team type produces a low response for the percentage of targets cleared due to the lack of tracking capability. The results of the analysis do not indicate that the QRF having an organic tracker UAV is a valuable asset. The sensitivity analysis performed only on the team types with a tracking capability produced similar results. For these team types, tracker launch and tracker speed produced no significant effects on the response variable. In order to produce an effect in the response variable from tracker launch and speed, we would recommend performing the analysis with a tracker UAV of greater capability.

We also discovered that the hard part of target clearance is not the interdiction of targets but the search for them, which relates directly to the search area size. How we search and the availability of assets continue be the main limiting factors in target acquisition. The number of team types and assets available is an area for future study to help determine an acceptable size of AO for mission accomplishment. We also found interdictor transit time to be a limiting factor for the cases where we studied team types with a tracking capability. The QRF can only clear the targets it can get to during the course of a mission and this is limited by how fast it can get to each target. The effect of increasing or decreasing interdictor transit time is an area worthy of future study. If it makes a difference in terms of the percentage of targets cleared, then an analysis of alternatives may be necessary to determine the best form of mobility for the QRF of the future.

The analysis also shows that while the tracking capability is better, the QRF possessing an organic tracking capability had no effect on the response. We also explored three team types to determine which factors affect the success of those team types in terms of the percentage of targets cleared. Those factors are team type and search area size. It may not be surprising to learn that as the search area increased, fewer targets were cleared. This is true regardless of the team type employed. While perhaps not useful as a prediction tool, the results of this simulation provide useful insights to a commander who is planning for a mission utilizing teams similar to the ones studied here. Based on the given AO, the commander may elect to employ a greater number of teams or partition the AO into smaller sections and employ teams in each partitioned area.

Through the analysis, we are able to show that possessing a tracking capability is superior to no tracking capability. When tracking is present in the team type, the number of targets cleared for a given mission is greater than when tracking was absent. Assuming that the surveyor is a national asset and there may only be one available for the AO and it may be unable to track until released by the QRF or tracker, the team types employed should include a tracker UAV. This would allow the tracker to be launched to the reported target location and get ''eyes on'' the location to track the target. If the target is not found, the tracker can then perform a search as the QRF approaches in an attempt to reacquire the target.

An area for future research is to study the effects of multiple teams in a given AO on the response. Specifically, a heuristic can be developed that can attempt to maximize the number of targets cleared by minimizing the time it takes for an interdiction team to arrive at a target location. This algorithm can solve a shortest path problem to the target from each team, identify the closest team, and then through an interface with SASIO an order will be sent to that team to begin the interdiction mission.

Also, more refined analyses can be performed with the inclusion of additional details of specific theater-relevant parameters, such as variable terrain types and their impact on QRF transits, time-varying or location-dependent sensor characteristics to reflect realistic capabilities, and the introduction of environmental impacts on the mission performance.

A valuable and complementary avenue for future work includes live-fly field experiments with real assets that could validate the proposed CONOPS and derived insights. Initial field experimentation efforts at Camp Roberts at quarterly field events have been conducted to utilize an autonomous Rascal UAV as the surveyor, a Raven UAV as the organic tracker asset, and a mounted team as the QRF. Further investigations and evaluation in field trials would enhance the operational relevance of the work presented in this paper.

Other areas where the SASIO analysis tool would be useful include the Navy's use of unmanned underwater vehicles (UUVs) and the USMC study of cargo UASs for battlefield resupply. The Navy envisions the UUV to have shallow water capability, stealth, and the ability to conduct ISR as well as antisubmarine warfare and mine-laying operations. The cargo UAS problem will be affected by numerous factors including range, payload, altitude and routes. SASIO provides the ability to perform a thorough analysis of the factor space for these problems and determine which factors will significantly affect the UUV and cargo UAS operations. Once these factors are determined a better CONOPS can be developed for their use. While these systems greatly enhance surveillance capabilities, their greatest contribution will be their ability to aid friendly forces in making decisions that will directly lead to an increase in the number of hostile targets cleared. This is one of the overall goals of these systems. Surveillance is simply a sub-problem of the surveillance and interdiction mission set.

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