MODELING AND ANALYSIS OF TACTICAL INSTALLATION PROTECTION MISSIONS

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ABSTRACT

Security of U.S. military installations is of high interest and operational importance to the U.S. military and allied forces. The Situational Awareness for Surveillance and Interdiction Operations (SASIO) model was developed to simulate the operational tasking of a single Unmanned Aerial Vehicle (UAV) and a ground-based interceptor used for searching, identifying, and intercepting potential hostile targets prior to reaching a military base. This research explores insights for the tactical employment of a UAV and an interceptor to combat potential hostile actions against a predefined area of interest. The design and analysis of experiments are used to create surrogate models that quantify the success rates of interception based on the employment strategies for both the UAV and ground-based interceptor and also characteristics of the mission. The results provide guidance for tactical employment of Blue Force assets, as well as provide alternative means to influence Red force behavior in a beneficial manner.

1 INTRODUCTION

Surveillance and interdiction (SI) problems are of great interest to the United States military due to the necessity to obtain pertinent information of potential hostile threats and to neutralize those threats upon their correct identification. The military utilizes numerous assets such as, but not limited to: Unmanned Aerial Vehicles (UAV), Ground Based Operational Surveillance Systems (GBOSS), and satellite imagery to aid in categorizing the entities' actions as threats or not. Upon detection and identification of possible threats, the military must take action to maintain security within the regions of operation. Situational awareness in such contexts is a necessary component in ensuring the utmost safety of our military forces.

This research uses the Situational Awareness for Surveillance and Interdiction Operations (SASIO) modeling software developed at the Naval Postgraduate School in support of relevant SI settings (Chung 2010). Situational awareness represents the knowledge and understanding of the environment and the actors within that environment. Use of the SASIO model is designed to support real-time employment strategies (decision support) and robust design strategies (analysis tool) to maximize the employment of surveillance and interdiction assets. The pertinent intelligence gathered from the employment of such assets could enable interdiction of threats as they may arise or before they engage.

The SASIO-based model for the tactical installation protection mission described in this paper provides a simulation and analysis tool based on currently available and forward-deployed assets (Byers 2010). SASIO can utilize current characteristics of surveillance and Quick Reaction Force (QRF) assets, such as a ground interdiction vehicle, to provide an employment strategy via multiple simulation iterations or provide real-time support through simulation iterations. The SASIO model can support many classes of SI contexts ranging from base protection, border protection, counter-drug operations and maritime operations with regards to counter-piracy efforts. These types of problems share common components that comprise any SI framework:

- Utilize surveillance assets to patrol the area and identify threats
- Detect and classify threats based on the intelligence gathered from the surveillance asset
- Transmit the information obtained by the surveillance asset to the QRF
- QRF can either investigate and/or interdict the potential threat

A benefit of the SASIO model is the ability to use the simulation as an experimentation tool to study the factors of relevance for performing SI operations. Examples of these factors include: speed of each asset (UAV, QRF), sensor characteristics (false positive and missed detection rates), and decisions pertaining to when the QRF should take action or aid in determining a secure location for a Forward Operating Base (FOB) within a hostile region. Results of the experiments conducted using SASIO will not only provide insight to the relevant factors in a SI mission, but also point out potential shortcomings of current technology and doctrine to provide meaningful insight in the context of these SI problems.

This research makes use of the SASIO model to explore a particular scenario of interest. The scenario involves the topographical constraints and road network found at Camp Roberts Army National Guard installation in California. The assets available in the scenario are a single UAV and a single QRF which are tasked with the mission of protecting a FOB. Numerous factors will be examined using design and analysis of experiments in order to analyze their significance in the proper employment of these forces to combat a potential threat to the FOB. This threat is characterized as a vehicle-borne improvised explosive device that can damage the FOB even if the threat does not reach the FOB. Section 2 briefly introduces the SASIO model. Section 3 provides an overview of the experimental design (including a description of the factors and response). Section 4 highlights the results. Section 5 discusses conclusions and future work.

2 SIMULATION MODEL

The area of interest (AOI) for this model is motivated by field experimentation efforts at Camp Roberts, California via the NPS-USSOCOM Field Experimentation Program (Bordetsky and Netzer 2009), where ongoing quarterly live experiments utilize aerial and ground-based assets. The scenario of installation protection centers around a "Y"-shaped road network with the FOB located at the intersection of the three roads, as depicted in Figure 1.



Figure 1: Camp Roberts road network

Each road is discretized into 250-meter segments, with node labels maintained and known to all Blue Force entities within the simulation. The resulting graph representation of the road network is an undirected graph linking each node to the adjacent nodes. This allows for objects, that is, Red and Blue ground elements, to transit throughout the area by moving from a single node to its adjacent node. The southern road is 1.5 km in total distance from entrance to the protected FOB location whereas the northern routes are each three km in length.

Both neutral and hostile vehicles are assumed to traverse the road network. The simulation considers three vehicles (one hostile and two neutral) entering the AOI and approaching the FOB location. Selection of which road each vehicle takes is drawn randomly from a uniform distribution, with and without replacement representing the "Road Selection" factor further described below. The discrete time at which each vehicle enters the AOI (via one of the entry nodes) is generated such that the inter-arrival times are geometrically distributed with specified mean. An additional consideration in the simulation model is the vehicle velocity as they traverse the roads towards the FOB.

As mentioned previously, the simulation model utilizes a UAV and a QRF to conduct the SI mission. The UAV employs a barrier patrol method (Washburn 2002) of flying around the FOB at a specified radius in its attempt to detect targets on the roads. Such search paths carry the advantage of historical use and well-developed analytical models (Benkowski, Monticino, and Weisinger 1991), particularly for antisubmarine warfare, and also captures the operational requirement to maintain surveillance off road as well (e.g., to detect dismounted entities such as a secondary "trigger man" or a camera man for enemy propaganda).

The speed at which the UAV can conduct this patrol is a relevant factor, comprising both the transit time from one node to the next as well as the loiter time which is how long the UAV must take to inspect a given node. Further, the UAV must detect and identify the vehicles on the road, and is limited by the quality of its sensor measurements. Though detection may be easy (and thus modeled as perfect), positive identification (PID) of the vehicle as neutral or hostile remains a challenge in theater. This imperfect identification is characterized by the false positive and false negative identification probabilities, Gamma and Rho, respectively.

The QRF has the responsibility of prosecuting a detected hostile vehicle. After transiting towards the detected vehicle at one node per time step, the QRF requires time (a.k.a. clear time) to engage and interact with the vehicle. Though the QRF could remain idle at the FOB location awaiting reports of a hostile vehicle, the ground unit can also conduct a patrol itself by moving down one road a given distance (e.g., 250m or 500m) and returning to the FOB, then moving down another, etc. This additional factor examines the benefit or penalty of committing the QRF to a given road (which might yield earlier detection and clearing of a hostile vehicle) while risking a delay in servicing a cue from the UAV on a different road.

3 DESIGN OF EXPERIMENTS

The SASIO model can be used to study the effect of many factors on the response variables of interest. Experimental design can be used to efficiently explore the design space. The SASIO model includes a graphical user interface (GUI), illustrated in Figure 2, that was built to allow experimentation by providing the user with easy-to-manage control over the factors of interest.

The response variable that is explored in this thesis is the probability that the threat is interdicted. Factor screening is performed first in order to reduce the dimensionality of the design space after which an additional experimental design and analysis on the remaining factors is carried out. The goal of the experimentation is to develop a mathematical model (surrogate model) that can be used to predict the number of objects interdicted as a function of the significant variables studied for the particular scenario of the three pronged road network and centrally located FOB.

00	SASIO:Insight Tactica	I Installation Protection
Insight Theater		
		Open Design Matrix CSV
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	Contermediate Nodes	Run Experiments
A T	•	
Description Tactical Installation Protection Mission Security of a Forward Operating Base (FOB) is of high interest and operational importance to the U.S. military and allied forces. The Situational Awareness for Surveillance and Interdiction Operations (SASIO) model		Status Window Welcome to SASIO:Insight! Selecting TactInstProtect (screening) Loaded 06DoeMatrixScreening.csv.

Figure 2: Screenshot of the graphical user interface

3.1 Model Factors

The factors and levels, which are investigated in this research, are illustrated in Figure 3. Each factor is a unique characteristic of the entities in the simulation. The factor levels, which are also shown in Figure 3, encapsulate the typical factor ranges that can change during military operations that utilize a UAV for surveillance.

Entities	Tune of Variables	Eastern	Levels	Description	
	Type of variables	Factors	Low Level High Level		
	Continuous	Velocity	[1,3]	Nodes / time step	
				Objects choose	
				road independent	
				from each other	
Objects				(2) or have a	
				single object per	
	Numerical	Road Selection	[1,2]	road (1)	
	A 11			E[Time between	
	Continuous	Time between Arrivals	[1,40]	Arrivals	
				Elight speed of the	
	Continuous	Velocity	[30 45 60]	Flight speed of the	
	Continuous	velocity	[30,43,00]	Probabilities	
	Continuous	Gamma	[0.045.09]	(identification)	
Agents (UAV)	Concinadas	Ganna	[0/0/0/0/0]	Probabilities	
	Continuous	Rho	[1-gamma , 0.45 , 1-gamma]	(identification)	
				Time steps for	
	Continuous	Loiter Time	[1,2]	loitering	
	Numerical	Radius	[250,1000]	Meters	
				If threshold in any	
				node is exceeded	
Agents (QRF)				via Probability	
				Map updating,	
				then QRF will	
				deploy to	
	Continuous	Deployment Threshold	[07 10]	investigate that	
	Continuous	Deployment Inreshold	[0.7,1.0]	Nodes purply from	
	Numerical	Patrol	[0 1]	FOR	
	Continuous	Clearing Time	[1,2]	Time steps	
	continuous	cleaning inte	V1xP1 V1xP2 V1xP3	Cross matrix of	
	Numerical	Prediction Model	V2xP2 V2xP3	object's velocity	
			V3xP3	and prediction	

Figure 3: Factor levels, ranges, and description.

Through varying the objects and entities, the model can provide insights regarding employment tactics to overcome the scenario threats. Utilizing experimental design and analysis to generate a surrogate model of this scenario can ultimately provide insights regarding employment tactics.

3.2 Response variables

The response variable of whether or not the given threat is interdicted is obtained as an output from the SASIO model. Because the SASIO model is a stochastic simulation, replications of each experiment are performed and the response variable is converted to a percentage metric over the replications. The percentage of threats interdicted is calculated based on the number of replications used for each design point.

Experimental design is the purposeful control of the input factors to the experiment to obtain their relationship (if any) with the response variables (Montgomery 2009). Utilizing efficient techniques, information collection for analysis purposes can be obtained in the most cost-effective manner. Experimental design allows for the control of factors through simulation that would be difficult to control in reality. As an example, this simulation allows the programmer to control the rate at which threats arrive. In practice, this is an "uncontrollable" factor, but in the context of this simulation, it can be systematically changed and thus provide insights that would otherwise be unattainable.

The 2^{12-5} fractional factorial design is used to conduct the screening experiments in this research. Factorial designs are an effective and efficient method for designing experiments intended for factor screening. Fractional factorial designs provide a nice alternative to running full factorial designs because they provide information on main effects and low-order interactions in far fewer experimental tests. After the initial screening experiments were used to reduce the dimensionality of the design, a D-optimal design (Myers and Montgomery 2002) with respect to the model generated from the screening experiment was used to conduct additional experiments.

4 **RESULTS**

The successful interdiction of a threat is represented as a Bernoulli random variable, which takes a value of zero if the threat is not interdicted and one if the threat is interdicted by Blue Force. The percentage of threats interdicted is obtained by counting the number of runs where the threat is successfully interdicted over the total number of simulation replications. This response, P, the probability of successful threat interdiction, is transformed with the logit function as shown in equation (1), which is the canonical link for the logistic regression model.

$$Y^* = \ln(\frac{P}{1-P}) = x\beta + \varepsilon \tag{1}$$

Standard multivariate linear regression is performed in JMP[©] on the transformed response. The linear regression model tests the following hypothesis:

$$H_0: \beta_0 = \beta_1 x_1 = \beta_2 x_1 x_2 \dots = \beta_n x_n = 0$$
, where *n* is the number of coefficients H_a : at least one coefficient $\neq 0$

where each β represents the coefficient of the linear regression term associated with main effects and twofactor interactions. Standard mixed stepwise regression is used to find the significant terms in the model. Figure 4 shows summary of fit and the analysis of variance for the final model selected by the stepwise linear regression process.

The R^2 value is 0.81 and Adjusted R^2 is 0.79. These values represent the amount of variability in the response that is explained by this model. Based on these metrics and a study of the residuals and other plots we conclude that the model presented is a satisfactory linear model. Since this model will be used to

represent the data for the screening process, the factors that influence this response must be obtained. Figure 5 represents the relative weight of each factor that influences the response variable.



Figure 4: Linear regression model of Log Odds transformation of percentage of threats interdicted

Term	Estimate	Std Error	t Ratio	Prob>	t
Rho	-0.062684	0.004203	-14.92	<.0001	*
Object_Velocity	0.0528697	0.00427	12.38	<.0001	1*
Road_Selection[-1]*Patrol[-1]	0.0295146	0.003926	7.52	<.0001	*
Rho*Object_Velocity	-0.028155	0.004331	-6.50	<.0001	*
Arrival_Time	-0.021945	0.003966	-5.53	<.0001	*
Arrival_Time*Road_Selection[-1]	0.0211875	0.004055	5.22	<.0001	*
Road_Selection[-1]	-0.018698	0.003839	-4.87	<.0001	*
Patrol[-1]	-0.018574	0.00388	-4.79	<.0001	1*
Object_Velocity*Patrol[-1]	-0.018242	0.003986	-4.58	<.0001	1*
UAV_Velocity*Rho	-0.017577	0.004238	-4.15	<.0001	1*
Arrival_Time*Patrol[-1]	0.0164039	0.004064	4.04	<.0001	1*
UAV_Velocity*Object_Velocity	0.0141289	0.004	3.53	0.0005	5*
UAV_Velocity	0.0138532	0.004252	3.26	0.0013	3*
Rho*UAV_Radius	0.013957	0.004295	3.25	0.0014	4*
Road_Selection[-1]*Object_Velocity	-0.012697	0.003983	-3.19	0.0017	7*
UAV_Velocity*Loiter_Time	0.0127783	0.004025	3.17	0.0018	3*
Loiter_Time	0.0120712	0.003894	3.10	0.0022	2*
UAV_Radius	-0.012786	0.004315	-2.96	0.0034	4*

Figure 5: Relative significance of each factor based on a linear regression of the Log Odds transformation of percentage of threats interdicted.

The results of the screening analysis indicate that the following main effects have the most impact on the percent of threats interdicted:

- Rho (the probability of false negative identification, i.e., incorrectly identifying a threat as neutral)
- Object velocity
- Road selection
- QRF patrol
- Inter-arrival time of the objects

Figure 5, which shows the relative weightings of each factor, demonstrates that the highest weighting factor is Rho, which directly relates to the classification of the threats by the UAV. This factor has a negative coefficient and therefore one can conclude that as one decreases this false negative identification error rate in the sensors, then the percentage of threats interdicted increases. That is, the better the sensor is at identification, then the better the chance of properly identifying the threat becomes (decreasing Rho by one unit increases the identification odds to 1.09). The next factor is the object's velocity, i.e., as the objects take longer to traverse from node to node, the probability of interdicting the threat also increases. If the Blue Force can perturb the speed of the objects in the AOI, then there is a higher likelihood of interdicting the threat. The next factor is the interaction between road selection and patrol. If the Blue Force can utilize checkpoints to ensure that a single object traverses a road per a given timeframe along with performing patrols, then the threat is more likely to be detected and detained.

In this study, the SASIO model simulated the design matrix fixing the object's velocity to the minimum value. Taking a subset of this output with the cross-validation design matrix, techniques were used to create a linear-regression model.

Exploration of the results indicated that the factor, object velocity, produced two distinct sets of results. Fixing the objected velocity speed to the low and high levels and refitting the model resulted in better predictions. An example of the predictive capability of the model is illustrated in Figure 6, which shows the cross validated predicted number of threats interdicted and associated prediction intervals.



Figure 6: Cross-validated predictions of percentage of threats interdicted

5 CONCLUSIONS

The tactical protection of a valuable installation provides an application with significant operational relevance in current military contexts. In particular, successful defeat of a vehicle-borne threat is of high importance given the devastating nature of such attacks. The presented work highlighted the development of a simulation model of the tactical environment, in which a single unmanned aerial asset is teamed with a ground-based interceptor to provide early detection and quick response to combat the possible threat. Various factors of interest, including the characteristics of neutral and hostile vehicle traffic as well as the capabilities of the surveillance and interdiction assets, and their interactions can influence Blue Force's performance in the installation protection mission. The road-based environment surrounding the installation was represented by a discrete graph, on which probabilistic models governed the likelihood and arrival of a threat while a stochastic process represented the uncertain motion of vehicles on the road network. Different employment strategies for the tactical UAV, i.e., varying patrol radii, and for the ground asset, e.g., whether or not to remain stationary at the base location, were also constructed and reflected in the simulation model.

This paper further described the use of Design of Experiments and regression analysis to efficiently determine and explore the relevant factors for the installation protection mission. The probability of successfully engaging, i.e., detecting, identifying, and interdicting, the vehicle-borne threat provided the response variable of interest. Transformation of this response via the logit function facilitated the use of linear regression to analyze the resulting data. Screening by means of a resolution-III fractional factorial design was performed and a D-optimal design in the significant factors and highlighted a number of significant factors, the most relevant including the speed of neutral and hostile vehicles in the AOI and also the UAV's likelihood of false negative classification of the threat. The resulting surrogate model was shown to adequately predict the effects of variations in the factors. Further investigations revealed additional operational insights and potential recommendations for standing operating procedures, including the beneficial use of checkpoints in regulating traffic near the protected installation.

Future avenues for study include refinements to the simulation model to account for realistic considerations such as terrain, different vehicle types, and improved or optimized surveillance methods, as well as the use of historical data, e.g., traffic patterns, to calibrate the model parameters. Examination of future concepts such as the deployment of additional UAVs to support the installation protection mission would also be of interest. Ongoing studies of other scenarios relevant to current military operations, such as oil derrick or convoy force protection, may also benefit from extensions of this work.

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