SENSOR LOCATION AND OPTIMIZATION TOOL SET (SLOTS)

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Abstract

With the proliferation of chemical and biological (CB) weapons, warfighter force protection, critical infrastructure defense, and installation protection are crucial aspects of today's battlespace preparation. Warfighters and analysts require decision support tools which can assist them in planning for force protection from these CB threats. These tools must ultimately support CB sensor optimization in terms of placement, sensor mix (point and standoff sensor systems), and existing C4 information analysis. SLOTS will model hazard movement over 3D terrain based on threat input and weather. It will then produce a sensor placement scheme based on agent dispersion characteristics, sensor characteristics, a sensor employment constraint set, and a predefined performance criterion (or set of criteria). Sensor placement heuristics will be used to form the constraint set. Models of the sensors, terrain, and agent transport will be used to generate data for evaluating the sensor placement schemes according to the specified performance criterion. Genetic Algorithms (GA) will be used to generate the sensor placement schemes. This effort will provide analysts and commanders with higher confidence in the monitoring capability of deployed sensors. The result will be a deployable, easy to operate tool that enhances the usability and reliability of deployed sensors into the larger concept of operations for CB protection.

Introduction

The relevance of a chemical and biological defense equipment development effort is measured, in part, by its ability to provide capability in one or more of the Joint Requirements Office's Chemical Biological Radiological and Nuclear (CBRN) core element areas - *Sense, Shape, Shield or Sustain*. Clearly the development and subsequent employment of detection systems largely contributes to our ability to *Sense* and to some extent *Shape* the battlespace. Our ability to accomplish this requires an extensive understanding of the interplay of the operational and technical challenges in employing sensor arrays to support detection, identification, and quantification of CBRN hazards.

While sensor technology continues to advance, chemical units are often limited in the number and types of sensor they are assigned. The challenge becomes understanding how to configure the sensors "in hand" to best accomplish the units mission. CB experts have evolved a set of rules governing this aspect of the *Sense* mission, grown out of years of experience. Many of the considerations for sensor placement are captured in doctrine and tactics techniques and procedures (TTP). Corollaries to these rules exist in the form of rules of thumb and lessons learned. The application of these rules in the field requires units to extrapolate between the ideal and reality. There is no method to optimize sensor distribution in real time to maximize the probability of mission success.

To this end the Joint Science and Technology program has funded the development of the Sensor Location and Optimization Tool Set or SLOTS. SLOTS will provide users with a tool that automates the process of sensor emplacement in the battlespace and will optimize the sensor placement solution based on user selectable parameters. The outcome will be a sensor employment plan, derived from convolving rules and high fidelity simulation of the environment and sensor performance, and applying advance artificial intelligence.

Background

Sense provides commanders with relevant hazard information at a specific time and place. Basic to *Sense* is the ability to employ sensor arrays to fulfill a commander's critical information requirements (CCIRs) regarding battlespace CBRN hazards. Complicating this objective is the reality of limited resources, technical and practical limitations, limited availability of analyst with required subject matter expertise, and the context in which sensors are employed. The question regarding what is the appropriate selection of sensors types, numbers, and locations depends on the interaction of the commander's intent or the mission, the enemy, terrain, troops, time and civilians (METT-TC), and available sensors. The chemical, biological, radiological, nuclear vulnerability assessment (CBRN VA) process provides a framework to answer the commander's priority intelligence requirements in support of the planning and execution of operations. Chemical units will know which and how many sensors they have based on the military table of equipment. By walking through the CBRN VA process they can hone in on the other factors associated with where to place them. The determination of the operational activity along the operational continuum (contiguous area of operations (AO) versus noncontiguous AO, fixed installation, temporary fixed installation - FOB, BSA, Firm, EAF, LOTS, or units maneuvering) establishes the context for sensor placement. This action designates the physical parameters of the problem space, taking it from the information environment, and begins the process of identifying named areas of interest (NAI), areas where the threat must be delivered to be effective, relevant to the high value assets requiring sensor coverage. An understanding of mission and key assets (people and equipment), in turn, dictates the avoidance, protection, and decon courses of action available to a commander and the CCIRs necessary to make decisions. This information forms the basis for developing fitness functions that will enable SLOTS to speak to the relative efficiency of different sensor arrays (types, number, and location). Additionally, the selection of AO, unit, and mission narrows the field of the end users and the time lines associated with their planning cycle. This information is critical to designing SLOTS graphical user interfaces (GUIs), processing (power and speed) requirements, and optimization algorithms.

Threat, analyzed during the first part of the CBRN VA process, constitutes a major data source of the sensor placement equation, as the agent type and method of dissemination will determine what sensors, under what conditions, can detect a hazard release, determine NAIs, and therefore determine "detect to" capabilities and limitations. Vapor hazards associated with non-persistent agents and liquid hazards resulting from persistent agents will trigger different sensors based on the type and detection threshold. An understanding of the enemy's order of battle detailing CBRN agents and methods of delivery, along with concept of employment limits the potential threat array. When considering non-state actor's NBC threats, consideration will have to be given to periods when weather is favorable for the release of agents, and will help shape NAIs for this type of threat. The result is a subset of threats that represent the answer as to **what is to be detected**. The characterization of the hazard release (liquid and vapor and concentration) will determine what is detectable and by **what type of sensor**. The fill rate associated with these weapons and cumulative hazard generated by a point or line source will help to define **the NAIs that will require protecting**. Finally, we are left with the question of **where to place the sensors**.

Sensor Location Optimization Tool Set

The initial effort of the SLOTS program will be to capture the set of heuristics that govern the emplacement of sensors in the battlespace. The SLOTS Handbook will be a compilation of these heuristics, reviewed and validated by subject matter experts in the Chemical and Biological Defense community. Aside from the benefit of producing a concise compendium of these heuristics, gathering this information will be the basis for the development of an automated application, SLOTS, that guides users through the CBRN VA process. The SLOTS GUI will walk the users through a decision tree, and pose questions that allow SLOTS to refine the outcomes of the NBC threat and vulnerability analysis. This will provide data necessary for use in vulnerability reduction measures—sensor placement.

Additionally, these user inputs will produce the data necessary to feed our models to provide the appropriate environmental context. Using SCIPUFF to generate the hazard threat (taking into account complex terrain and meteorological conditions) convolved with the mission data resulting from the CBRN VA and the CCIR bounding this process, SLOTS will generate a first order sensor deployment plan. Key to this operation is the ability to represent the performance of the array of sensor systems available to the commander. In going through the CBRN VA process, the sensor types required to support the mission, and the allocation of these is determined. SLOTS will utilize components of the Chemical Biological Dial-A-Sensor ™ or CB DAS to simulate the performance of a given sensor system. CB DAS is a component of the ITT Industries developed CB Simulation Suite, and provides a high level performance representation of most classes of available sensors. CB DAS can be easily extended to include new sensors, or conceptual sensor types.

During the SLOTS development effort, the results of automating sensor placement will be reviewed by Chemical Soldiers (some of the aforementioned SMEs). These Soldiers will be asked to employ the techniques outlined in doctrine and TTPs to arrive at a sensor placement plan for a sample mission. This same mission will be run through the SLOTS application. The result will be compared. This provides an initial verification of the process automation. Until this point automation has been the main thrust of the effort. Sensor placement plan optimization is the ultimate objective for the SLOTS, employing advanced artificial intelligence (AI) techniques. Verification of our process automation is critical, since with most AI techniques, the validity of the results is limited by that of the inputs (garbage in – garbage out).

To optimize our solutions, genetic algorithms (GA) will be used to generate the sensor placement schemes. This global solution space search technique is well suited for solving complex optimization problems generally stated as: given a set of N possible solutions, find the subset of M solutions to optimize some pre-determined measure of performance subject to certain constraints. Such is the case in determining where sensors need to be placed. A genetic algorithm is initialized by generating a large number of solutions to the problem and it then searches for improved solutions via biological evolution principles. Solutions are selectively recombined and stochastically altered to produce increasingly better solutions and weeding out poor ones to converge on a near optimal solution as determined by a performance criterion. Other optimization approaches that could be used to attack this problem include:

complete enumeration (i.e., exhaustive search), gradient descent, and heuristic methods. For large, realistic problems, exhaustive search suffers from combinatorial explosion while a gradient descent approach can be problematic due to local maxima (minima) and discontinuities in the search space. Thus a heuristic technique such as a genetic algorithm is an attractive alternative (Padula and Kincaid, 1999).

A genetic algorithm (GA) searches for solutions via the biological evolution principles of Natural Selection (i.e., survival of the fittest, crossbreeding, and mutation). The term genetic algorithm comes from fact that solutions are represented as strings of values analogous to chromosomes and genes. A GA starts with a set of initial solutions (typically via random solution generation) and produces increasingly better solutions by selectively combining (called crossover in GA terms) and stochastically altering (called mutation in GA terminology) existing solutions and weeding out poor ones to converge on a near optimal solution as determined by a specified performance criterion (referred to as the fitness function). This amounts to searching a large multidimensional (and possibly discontinuous) search space to find the solution with the best fitness function value. The general genetic algorithm procedure is represented in Figure 1 (Mitchell, 1997). The following provides a detailed description of the GA process and how it would be implemented for the sensor placement problem.

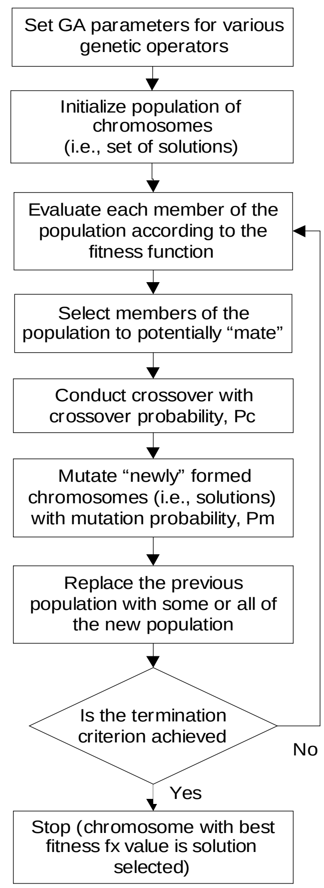

Figure 1. The basic genetic algorithm procedure

Sensor Placement using Genetic Algorithms

To reiterate, the objective of SLOTS is to provide an analyst with the tools to optimize the placement of a set of sensors given certain environmental conditions and employment factors. The proposed research will employ a genetic algorithm to search the sensor location space, subject to constraints, with the overall sensor placement scheme being evaluated according to a optimization criteria. We will develop the capability to define and generate a large grid representing potential sensor locations which will be linked to the transport model representing the dispersal of agent influenced by terrain and meteorological conditions as well as agent attack scenarios (Dhillon, Chakrabarty, and Iyengar, 2002). This will facilitate the evaluation of sensor placement schemes according to the specified fitness function. The granularity of the grid (distance between consecutive grid points) will be determined by the accuracy with which the sensor placement is desired. Methods will be developed to visualize the transport data in conjunction with the sensor placement scheme. The remainder of this section walks through the implementation of a genetic algorithm describing the process and how it would be implemented for developing sensor placement schemes.

The first step in the GA process is to determine the structure of the solution and encode it as a string of values representing the decision variables associated with the problem. In the case of sensor placement, the solution represents the placement of sensors (similar ones in the homogeneous case and different ones in the heterogeneous case) within an NxM dimensional grid overlaid on a piece of terrain. One traditional sensor placement scheme would be to encode the genetic algorithm as a chromosome with each gene in the chromosome representing the presence or absence of sensor i at location j. Figure 2 illustrates an example of a solution structure for two sensor types within a simple 2x2 grid (1 represents the presence of the sensor at a particular location, while a 0 represents its absence).

Sensor A Loc 1,1	Sensor A Loc 1,2	Sensor A Loc 2,1	Sensor A Loc 2,2	Sensor B Loc 1,1	Sensor B Loc 1,2	Sensor B Loc 2,1	Sensor B Loc 2,2
0	0	0	1	0	0	1	0

Figure 2. Example Sensor Placement Solution Structure for Two Sensors

However, this representation exhibits similar problems to that of the exhaustive search in that it suffers from combinatorial explosion as the grid granularity increases. Additionally traditional mutation operations such as "flip a bit" tend to result in invalid solutions where sensors appear and disappear.

An alternate gene encoding is much more practical for this solution space. Consider a grid of N x M, and an array of sensors (p of type A and q of type B). A locator function provides an integer identifier for a grid space, such that a position of x,y returns the value of y * M + x . With this locator transformation, the chromosome is represented as a single array of integers size p + q. The simple 2x2 grid now would be encoded as shown in Figure 3.

Sensor A (Loc 2,2)	Sensor B Loc 2,1
4	3

Figure 3. Alternate Example Sensor Placement Solution Structure for Two Sensors

Aside from the obvious physical memory savings of this representation, additional gains include the ability to perform meaningful "mutation" operations such as "Move Sensor A one location to the West (subtract one from its current location)" and "Move Sensor B one location to the South (add N to its current location)"

The following example illustrates why an exhaustive search methodology is inappropriate for a modestly sized problem (let alone a more realistically sized problem). Let us assume we have 3 different sensors and a 5x5 grid. The upper bound on potential solutions would be 3.78x1022 (under the assumption that a sensor 'could' be placed at every point in the grid). Even if a computer could provide 1 million calculations a second, it would take over a billion years to evaluate every one of the potential solutions to determine the optimal sensor placement scheme. This clearly illustrates the need for a heuristic technique for solving 'real world' problems in an appropriate timeframe.

The solution set (i.e., collection of chromosomes) is called the population. The initial population is composed of a large (typically ranging from 100 to 1000) diverse (randomly created) set of solutions. An initial population of solutions will be generated, consisting of multiple potential sensor placement schemes.

Each solution (i.e., chromosome) in the population is then evaluated by a defined performance criterion (i.e., fitness function). The fitness reflects how well the sensor placement scheme solves the problem. Various sensor placement scheme performance criteria will be considered with a subset being investigated during this research. The fitness function value is then recorded for each solution in the population.

This step creates a 'breeding population' by selecting, probabilistically from the population based on their fitness function value, those solutions to selectively combine (i.e., chromosomes who will 'mate') and how often. The selection process provides the better solutions an increased chance to combine while also affording (albeit with a lower probability) less fit members (with potentially critical characteristics) an opportunity to mate as well. Popular selection techniques include the Weighted Roulette Wheel, Rank Selection, and Tournament Selection. During this step, sensor placement solutions will be selected to combine with other sensor placement solutions to create new sensor placement solutions. The manner is which those solutions are combined is addressed next.

In order to improve the current sensor placement solution set (i.e., population), genetic algorithms commonly use two genetic operations called crossover and mutation. Crossover can be viewed as an operation promoting genetic qualities that are already present in the population. Conversely, mutation promotes diversity within the population by introducing new qualities in an attempt to increase fitness.

The crossover operation exchanges information from two 'parent' solutions (i.e., chromosomes) from the breeding population. Typical crossover methods include Single-point, Two-point, and Uniform. Figure 4 illustrates how Single-point crossover would work for a sensor placement example for two 'parent' solutions creating two 'child' solutions. The crossover point is selected at random and crossover is conducted by exchanging portions of the solution of the parents to create subsequent solutions (called children). This process is repeated 'population size' times.

Crossover Point

Parent 1	3	16	5	32	153	2	35	6
Parent 2	35	7	253	86	33	103	88	76
					CP			
Child 1	3	16	5	32	33	103	88	76
Child 2	35	7	253	86	153	2	35	6

Figure 4. Example of Single-point Crossover for Eight Sensor Solutions

Since crossover can only rearrange information already in the solutions, mutation (i.e., stochastic altering) is a method that circumvents this problem, allowing the examination of potentially fruitful portions of the solution space. Once child solutions are created, the mutation operator can randomly change portions of the solution (i.e., genes) in the children with some, typically, very low probability (e.g., .001). Figure 5 illustrates the mutation of gene 3 of Child 1 in Figure 4. This is equivalent to moving the third sensor in the array one grid cell to the

Child 1	3	16	5	32	33	103	88	76
Child 1'	3	16	6	32	33	103	88	76

Figure 5. Example of Mutation of a Solution

The previous set of sensor placement solutions (i.e., generation) will then be replaced with the new solutions via a replacement strategy. Replacement is the manner in which the next set of solutions (i.e., chromosomes) is determined. Replacement techniques include: Generational (i.e., replace the entire previous population), Elitist (always retain the most fit chromosome), Steady State (replace a small portion of the population), and Steady State without duplicates.

The genetic algorithm process steps continue until a termination criterion is achieved. There typically are five common termination criteria from which to select:

- When the population has converged largely to a single chromosome.
- When improvement in the average fitness (or maximum fitness) of the population has leveled off.
- When a predetermined number of generations has occurred.
- When a certain amount of time has elapsed.
- When a solution meets or exceeds some measure of fitness.

Once the termination criterion is achieved, the solution (i.e., chromosome) with the best fitness function value provides the sensor placement solution.

The use of genetic algorithms for sensor placement is novel within the Chemical Biological Defense arena. However, GAs have successfully been employed in wireless communication node placement applications and a growing list of other successful implementations. The SLOTS development effort will make use of an existing genetic algorithm library developed by Professor Matthew Wall at Massachusetts Institute of Technology. Professor Wall's, **GAlib**, has been used in a number of commercial, government and academic products, such as Intuit's financial products and SAS/MarketMax's retail space planning system. Because GAlib is at the heart of these larger user-base applications it is extremely well documented.

Conclusion

The SLOTS development team has a few challenges to be addressed during the two year development period. The goal of this effort is to deliver a tool that optimizes sensor placement based on militarily relevant fitness functions. These may vary from – "minimizing time to detect" to "maximizing the probability of detection" and then combinations thereof, all within the bounds of the appropriate operational constraints. This aspect places huge requirements on the underlying architecture and software design, for SLOTS to have the broadest application. Aside from the technical aspects of producing a software tool that is user friendly, meets all the runtime, operating system, and network worthiness requirements significant deliberation will be focused on determining how good is the SLOTS final solution. A failing of GA applications is the tendency to converge on false-maxima. To safeguard against this behavior, a process for validating solutions will be developed.

The SLOTS effort will develop a sensor placement and optimization tool capable of supporting the warfighter and analysts in generating a sensor placement plan to best accomplish the *Sense* mission, protecting the force and critical assets. SLOTS will offer a structured and repeatable automated methodology to achieve optimized sensor placement in support of deliberate planning, and by extension resource allocation studies. This development will leverage previous accomplishments in CB sensor and hazard transport modeling, applied artificial intelligence, and software engineering.

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