

Sensor-netting algorithm for CB threat mapping

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ABSTRACT

Large networks of disparate chemical/biological (CB) sensors, MET sensors, and intelligence, surveillance, and reconnaissance (ISR) sensors reporting to various command/display locations can lead to conflicting threat information, questions of alarm confidence, and a confused situational awareness. Sensor netting algorithms (SNA) are being developed to resolve these conflicts and to report high confidence consensus threat map data products on a common operating picture (COP) display. A phase I SBIR study to develop a conceptual design for a SNA was recently completed. Mathematical approaches for assigning uncertainty to incoming data streams, doing spatial/temporal correlation of point and standoff sensor data (via vector translation based tomography), estimating uncertainty for threat maps, and consistency checking between the consensus threat map result and the individual input data streams were developed. A set of simulation environment tools for testing the SNA, including a simple threat model, sensor models, and fused and un-fused COPs, were also prototyped during phase I. The SNA development and simulation based testing will continue during the phase II effort, which was just awarded.

Keywords: sensor, netting, algorithm, fusion, tomography, map, uncertainty, consistency

1. INTRODUCTION

Networks of chemical/biological (CB) sensors, MET sensors, and intelligence, surveillance, and reconnaissance (ISR) sensors reporting to various command/display locations can lead to conflicting threat information, questions of alarm confidence, and a confused situational awareness. Sensor netting algorithms (SNA) are being developed to resolve these conflicts and to report high confidence consensus threat map data products on a common operating picture (COP) display. A phase I SBIR effort to develop the mathematical approach and basic design for a SNA was recently completed. A portion of the phase I SNA design effort is presented within this paper, starting with a discussion of challenges and requirements in section 1, preprocessing of the various network sensor input data streams in section 2, fusion of point and standoff data using tomography in section 3, data consistency checking in section 4, and SNA data products in section 5. A set of simulation environment for testing the SNA was also prototyped during phase I and is presented in section 6 along with our plans for the phase II research effort.

The authors from MESH performed the SBIR phase I work and held discussions and reviews with the authors from the U.S. Army at APG, who advised MESH on the SNA needs and goals.

1.1 Opportunities and challenges with data from networks of sensors

Higher confidence threat map results and lower false alarm rates are the anticipated outcomes from properly fusing data together from battlefield networks of CB, MET, and ISR sensors. There are many challenges for the data fusion process including:

- Utilization of both standoff sensor (path integrated, line-of-sight measurement) data and point sensor (measurements at one location in space) data, as well as other non-traditional sensors (e.g., terrain, MET, etc. data), within one algorithm process in order to obtain high confidence threat detection results
- Resolving conflicting sensor data and detecting/rejecting erroneous sensor data
- Achieving higher confidence results than the individual sensors (i.e., the un-fused data) within the network
- Succinct and timely visualization of threats on the common operating picture (COP)

This paper focuses on a tomography based SNA solution that addresses all of these challenges. By converting both point and standoff sensor measurements to vectors, the data can be fused. By checking consistency between the tomography generated threat map result and the individual input sensor data streams, erroneous sensor data can be detected. By combining the uncertainties for all input data within the tomography process, the uncertainty of the tomography output map is obtained. By buffering the various sensor data over time, frequent map updates can be calculated by using all recent measurements for timely visualization and prediction. All of these will be further explained in the sections that follow.

1.2 Specific sensor netting requirements

Our development work started from the following SNA requirements:

- Correlate and fuse weighted signal outputs from multiple point and standoff sensors, that come and go off-line at arbitrary times
- Use metrics that provide for accurate identification/classification and system wide correlation of sensor data
- Provide a measure of confidence with all SNA results (SNA results should have higher confidence than the results from individual sensors)
- Reduce false alarms for fused results as compared to individual raw sensor data streams
- Utilize terrain and other non-traditional sensor data to enhance the data fusion process
- Cue follow-on assets for additional measurements of the threat

The tomography based SNA design developed in Phase I can address most of these requirements; however, this paper is limited in scope to discussion of weighted fusion of point and standoff data, providing confidence for SNA results (i.e., estimation of threat map uncertainty), and reduction of false alarms.

1.3 Sensor netting algorithm (SNA) design

The phase I SNA design solution, as shown in Figure 1, includes the following key process steps:

- Input data preprocessing to characterize noise and bias errors, assign uncertainty to all measurements, and detect/reject erroneous sensor data
- Threat map calculation via a tomography data fusion process which accepts both point and standoff data, adjusts sensor data for measurement age/MET conditions (i.e., a method of time correlation), and determines the threat level result
- Threat map post processing for checking sensor consistency (with feedback to the input preprocessing), producing COP data products, and cueing following-on assets

It is not possible to discuss all aspects of this SNA design within this paper. The Sensor Amalgamation Mapping by MESH, Inc. (SAMMI), a modified tomography process, which is the core of the SNA, is discussed in enough detail to:

- Show how both point and standoff sensor data can be treated as vectors
- Discuss how the weighting of various sensor data within the tomography process can be achieved
- Show the math for estimating the tomography result uncertainty
- Show the math for consistency checking between the input data and the tomography output threat map result

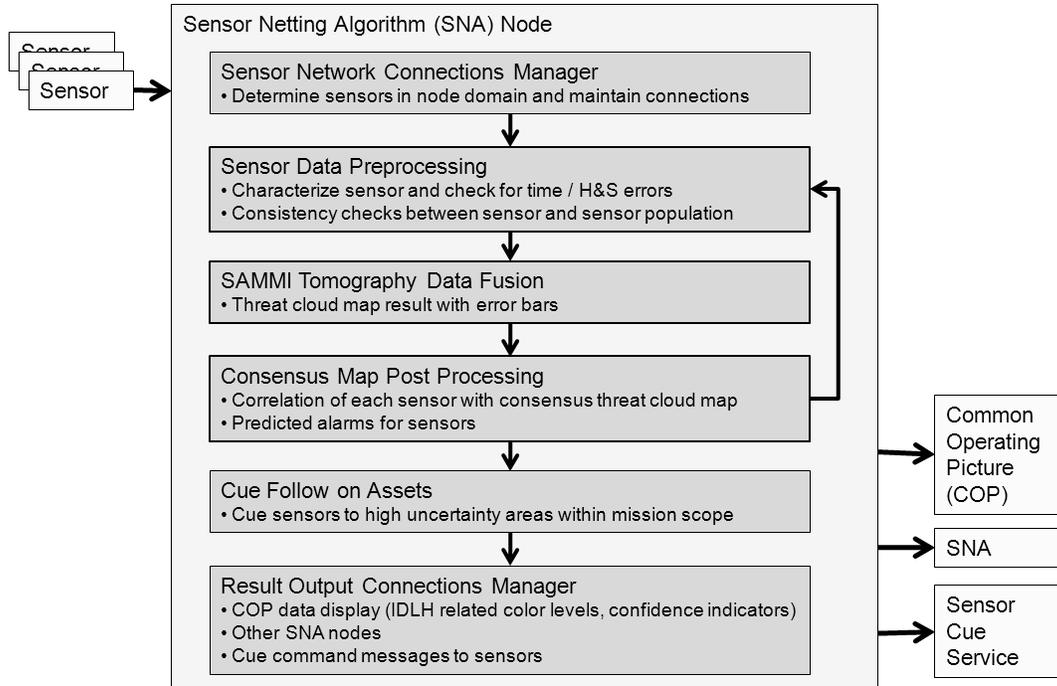


Figure 1. Prototype SNA process block diagram showing key components, input streams, and outputs.

2. PREPROCESSING OF INPUT DATA TO ESTIMATE UNCERTAINTY

In order to determine the overall confidence level for threat map results, and in order to “weight” the data together in the fusion process, it is necessary to understand the uncertainty or error bars on every individual sensor measurement result within the reporting network of sensors. Additionally, the monitoring of sensor uncertainty (or noise) with respect to the population of that particular type of sensor can also be used to detect and reject bad sensor data.

Several strategies were developed for estimating these uncertainties for the various incoming sensor measurements. These include the following:

- Calculating each sensor’s raw signal noise (i.e., standard deviation of the signal over some window in time) during non-alarming periods, and assuming that this noise level is the uncertainty for the result (e.g., for a quantitative point sensor, the noise is assumed to be the concentration uncertainty)
- Using laboratory characterization testing to create a look-up table of uncertainty for a given type of sensor and as a function of various environmental conditions
- For the case of qualitative sensors (e.g., a yes/no alarm chemical point sensor), the uncertainty may be estimated as half way between the minimum detection limit of the sensor and the highest expected concentration for the detected agent (e.g., some fraction of the vapor pressure for the current ambient temperature). However, it is expected that sensor manufacturers will be required to provide “raw signal taps” to support SNA needs.

The concept of continuous, real-time, characterization preprocessing of the input data for a given sensor is shown in Figure 2.

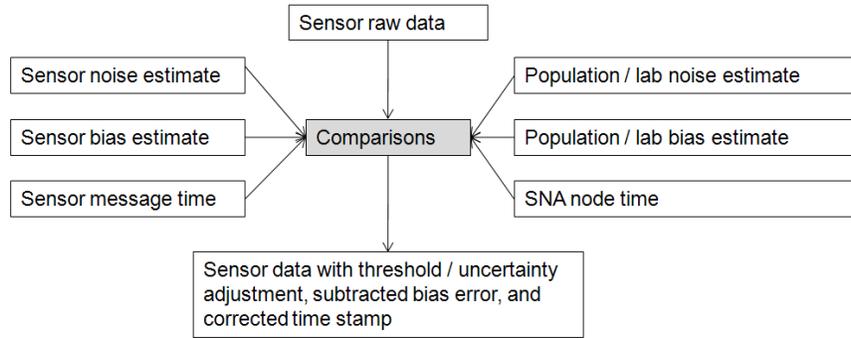


Figure 2. Concept of checking individual sensor data streams against the available total population of sensors for that particular type of sensor. The goals are to estimate the uncertainty for each sensor measurement and to detect bad sensors (i.e., outliers with respect to the population typical performance).

3. A TOMOGRAPHY PROCESS TO PRODUCE THREAT MAPS FOR THE SNA

Tomography is the process of taking path-integrated measurements, from various sensing vantage points, and turning the data into a map of some property at individual points in space (e.g., a concentration map made from a collection of path-integrated measurements). The SAMMI tomography used within the SNA is a modified Algebraic Reconstruction Technique (ART) that is designed to work with both point and standoff sensor data. ART was selected because it performs best for sparsely sampled, noisy data, from a limited number of vantage points¹. The modifications were primarily made to the projection matrix calculation. The details of the tomography process are explained in order to be able to discuss the weighting of sensor data and the uncertainty calculation for the map results.

3.1 Grid space

The region of interest that contains the assets is called the “grid space” and it is made up of voxels (i.e., 3D pixels). The resolution or minimum size of these voxels is dependent on the density of the sensors (or the spatial coverage of the standoff sensors) within the network. With low density networks, the SAMMI tomography functions as a smart triangulation algorithm, and for higher density networks, it functions as a 3D concentration map calculation engine. An algorithm for automatically defining the grid space based on the sensor network configuration is still under development.

3.2 Point sensor and standoff sensor measurements as vectors

It is easy to understand standoff sensor, path integrated, concentration-length (CL), measurements as vectors. It is not as easy to understand how point sensor data can be converted to vectors.

Point sensor data are converted to vectors using the process shown in Figure 3. A point sensor measures a strip of air during its measurement integration time. This strip of air has a direction (i.e., wind direction). The length of the strip of air is the wind velocity multiplied by the sensor integration time. This “strip” is a path integrated concentration vector, which is the same type of measurement that standoff sensors make. Tomography is the process of converting sets of path integrated measurements (e.g., CL vectors) into maps of some property as a function of location (e.g., concentration maps). By converting point sensor data to CL vectors, we have provided a means for correlating and fusing point and standoff data within the same process.

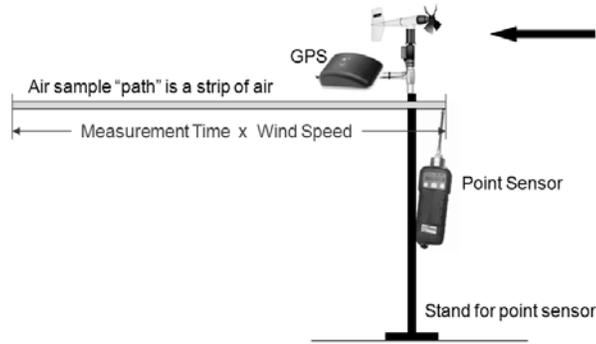


Figure 3. Point sensor measurements are converted to path integrated concentration (CL) line segment vectors using the wind velocity and sensor integration time. In an actual sensor network, the local wind velocity for a given point sensor may be estimated using a MET model and a network of a few wind sensors. A cross sectional area “domain” (e.g., 1 m^2), which is analogous to a standoff sensor instantaneous field of view (iFOV), must be assumed for the point sensor line segment vector.

3.3 Wind correction by vector translation based on measurement age

SAMMI tomography maps are calculated at a chosen “map time”. Map times may be now or some short time into the future (e.g., 15 seconds into the future for the purpose of prediction). Some sensors are able to provide frequent updates (e.g., a 1 Hz point sensor), while other sensors may take 30seconds to cover their field of regard (e.g., a scanning standoff sensor covering 0 to 360 deg of azimuth by 10 deg of elevation). Therefore some measurements may be older than others at the time of a map calculation. The age of each measurement, combined with the MET data, may be used to translate the measurement to the approximate proper location for the map calculation time. Furthermore, the collection of all recent measurements (e.g., the last 30 seconds of data, depending on conditions) may be translated in this way to spatial and temporally “correlate” the collection of measurements. Figure 4 shows the vector translation concept as described. For the standoff sensors (green boxes), the most recent measurement vector is connected to the sensor. As the standoff measurements age, they are translated downwind based on the average wind velocity during each measurement’s age time. For the point sensors, the recent line segment vectors are also translated away from the point sensors as they age. This translation process:

- Enhances data correlation by overlaying more measurements in space (the intersection of vectors from different sensors is the definition of correlation in this case - we want multiple sensors to agree on the threat location, which reduces false alarms)
- Corrects for wind distortion, which would otherwise occur if the old and new measurements were simple mixed without using vector translation
- Allows for the usage of recent point and standoff measurement data as opposed to only the current measurement result. This is especially powerful for enhancing the range of influence for point sensor data within the threat mapping process

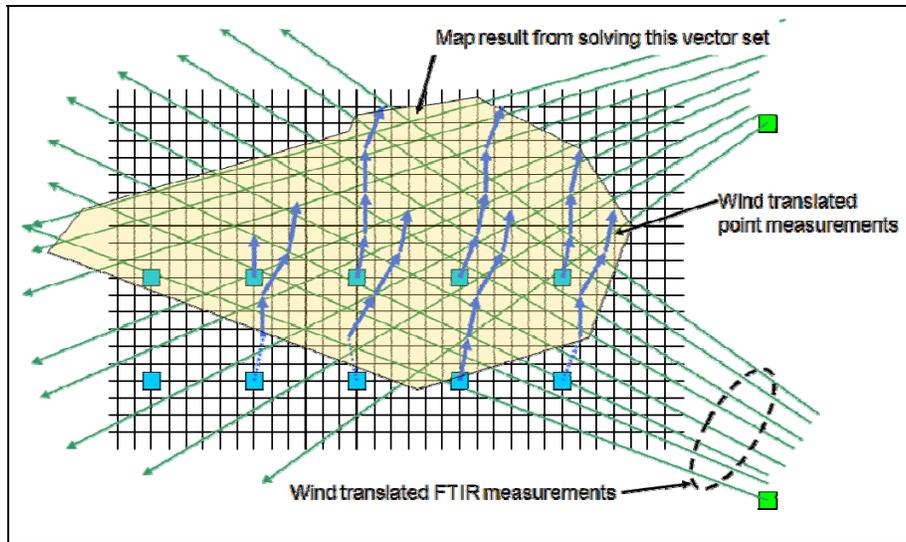


Figure 4. The set of recently buffered point and standoff sensor CL vectors are translated based on average wind velocity and age. This allows for the point sensors to have a greater domain within the solution space (as shown by the trails of blue vectors).

3.4 Projection matrix for mapping sensor measurement vectors to the grid space

The collection of translated measurement vectors must be mathematically “mapped” into the grid space of interest. This is done by calculating the projection matrix, which determines the weighting factor between every measurement and every voxel¹. Unlike standoff sensor measurements which are only limited by the terrain, the SAMMI tomography process must limit the range of the point sensor vectors which typically have a very short length (e.g., a few meters to tens of meters). The projection matrix concept is shown in Figure 5.

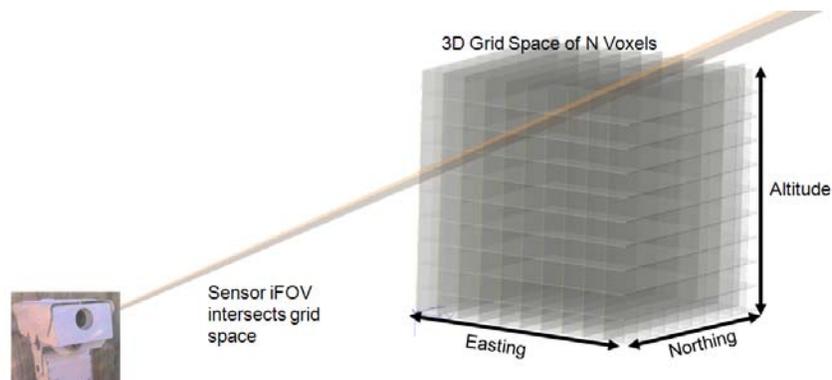


Figure 5. A standoff sensor path integrated measurement is shown passing through a UTM coordinate grid space. The standoff sensor’s iFOV is shown as an elongated pyramid shape for a rectangular detector element.

The projection matrix is calculated by integrating along the line-of-sight iFOV for a standoff sensor:

$$\left(\begin{array}{c} \uparrow \\ \text{Projection Matrix} \\ \text{P x N} \\ \downarrow \end{array} \right) = \left(\begin{array}{cccc} \frac{1}{A_0} \int_{iFOV_0} \text{Basis}(S - \text{Voxel}_0) dS & \frac{1}{A_0} \int_{iFOV_0} \text{Basis}(S - \text{Voxel}_1) dS & \dots & \\ \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \frac{1}{A_{P-1}} \int_{iFOV_{P-1}} \text{Basis}(S - \text{Voxel}_{N-1}) dS \end{array} \right)$$

P = number of CL vectors
N = number of grid voxels

(1)

The integration is weighted using a basis function that is based on the distance between the vector (i.e., iFOV domain) and the center of a given voxel. The integration is normalized by dividing by the average cross sectional area, A, which is the iFOV spot size at the distance to the center of the voxel. A similar process is used for integrating the point sensor line segment vector data. There is one row in the projection matrix for every sensor measurement and one column for every voxel within the grid space.

3.5 Tomography using the Algebraic Reconstruction Technique (ART)

The goal of the ART method is to find an object vector (e.g., chemical threat cloud concentration map) that reproduces the input data set, which is the array of all concentration path-length (CL) data vectors from all the reporting sensors in the network, as shown in the following matrix equation:

$$\left(\begin{array}{c} \uparrow \\ \text{CL "Vector"} \\ \text{P x 1} \\ \downarrow \end{array} \right) = \left(\begin{array}{c} \uparrow \\ \text{Projection Matrix} \\ \text{P x N} \\ \downarrow \end{array} \right) \left(\begin{array}{c} \uparrow \\ \text{Object Vector} \\ \text{N x 1} \\ \downarrow \end{array} \right)$$

Units of concentration x distance Units of distance Units of concentration

(2)

The dimensions of each vector or matrix are indicated within the equation terms by a combination of letters and arrows (e.g., "P x 1", meaning a vector of size "P" of CL measurements from the sensors). The basic ART process is to solve for the object vector using an iterative process, where the object vector at iteration q+1 is given by¹:

$$\left(\begin{array}{c} \uparrow \\ \text{Object Vector} \\ \text{N x 1} \\ \downarrow \end{array} \right)_{q+1} = \left(\begin{array}{c} \uparrow \\ \text{Object Vector} \\ \text{N x 1} \\ \downarrow \end{array} \right)_q + \text{Adjustment}_i \left(\begin{array}{c} \leftarrow \text{Projection Matrix, row } i \\ \text{1 x N} \\ \rightarrow \end{array} \right)^T$$

Adjusts part of object vector that is effected by measurement CL_i

(3)

where the "adjustments" are error terms for each sensor measurement:

$$\text{Adjustment}_i = \frac{CL_i - \left(\text{Projection Matrix, row } i \right) \left(\text{Object Vector} \right)}{\left| \left(\text{Projection Matrix, row } i \right) \right|^2}$$

(4)

Note that “i” is the index denoting a specific sensor CL measurement (i.e., $i = 0$ to $P-1$). For each iteration, the object vector must be updated “P” times for all values of “i”. This is done in a random order.

The output of the tomography process is the concentration result for the detected agent (or class of agent) for each voxel (i.e., each element of the object vector) within the grid space region of interest. The tomography process reduces false alarms by requiring that each voxel result be confirmed by agreement between data from at least two or more sensors. The collection of voxels that contain the threat cloud can be converted to various data products from concentration maps to threat boundary maps, as discussed in section 5.

3.6 Weighting of the input data

One of the ideas that is currently being pursued for weighting the individual sensor CL data using the sensor uncertainty is presented. The idea is to set the adjustment factor to zero if the absolute value of the difference between the CL_i and the tomography process estimate of the CL_i is less than the sensor uncertainty (U_{Sensor}). This effectively limits noisy sensors to only making course adjustments to the threat map solution. Low noise sensors will be allowed to make smaller adjustments to the object vector (i.e., map result).

3.7 Estimating the concentration map uncertainty

A mathematical approach to estimating the SAMMI tomography concentration map result uncertainty was developed during phase I. The problem is to apportion the uncertainty for each sensor measurement among the voxels that are affected by that measurement, as shown in Figure 6, for a particular CL measurement. This approach includes the proper uncertainty weighting factor for each voxel, which is given by the partial derivative of the concentration calculation with respect to the CL measurement.

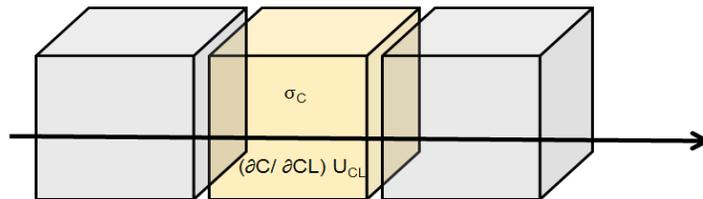


Figure 6. A path integrated measurement, CL , with uncertainty, U_{CL} , is shown passing through 3 voxels within the grid space. The problem is to fairly distribute the measurement uncertainty among these voxels. The weighting factor for each voxel is related to the derivative of the “tomography process concentration calculation” with respect to the measurement CL .

The concentration uncertainty for each voxel is the square root of the sum of the squares of the two basic error terms. These terms are the sensor input data measurement errors and the tomography convergence variation (i.e., tomography process error):

$$U_{\text{voxel}_j} = \left(\sum_{\text{CL}_i} \left[\frac{w_{ij}}{(PM_i)(PM_i)^T} U_{\text{CL}_i} \right]^2 + \sum_q (C_q - C_{\text{avg}})^2 \right)^{0.5}$$

All point and standoff measurements that pass through voxel j
Selected iterations post-convergence, concentrations are for voxel j

(5)

where U_{voxel_j} is the “jth” voxel concentration uncertainty in $[\text{mg}/\text{m}^3]$, U_{CL_i} is the CL uncertainty for the “ith” measurement from a particular sensor in $[\text{mg}/\text{m}^2]$, w_{ij} is the projection matrix coefficient for measurement “i” and voxel “j” in $[\text{m}]$, PM_i is the projection matrix row which contains the coefficients for all grid space voxels for the “i” measurement in $[\text{m}]$, $[w_{ij} / ((PM_i)(PM_i)^T)]$ is the partial derivative of concentration with respect to the CL in $[\text{m}^{-1}]$, and $(C_q - C_{\text{avg}})^2$ is the variance of the post convergence concentration (from a subset of iterations given by q) for the “jth” voxel in $[\text{mg}/\text{m}^3]$.

This method of estimating the map result concentration uncertainty will be implemented and evaluated during phase II by using different levels of input sensor data noise. A similar process will also be used to propagate line-of-sight direction errors and sensor location errors through the tomography process in order to determine location error bars for the threat map.

4. CONSENSUS THREAT MAP CORRELATION WITH THE INPUT DATA

The covariance consistency checking concept, as used in the processing of missile tracking measurement data, was reviewed and used to inspire an approach for consistency checking for SNA threat map results^{2,3}.

A mathematical approach for checking consistency between individual sensors and the consensus threat map was developed in phase I. The idea is to compare each sensor response to the SAMMI tomography concentration map result using a correlation coefficient:

$$\text{Sensor A correlation} = \frac{\text{covariance}(A, C)}{\sigma_A \sigma_C}$$

Filtered sensor input to SAMMI
SAMMI result at location A

(6)

where A is the time sequence of data from the point sensor A, and C is the recent sequence of concentration results (taken from multiple consecutive maps) for the location of the same sensor. A similar approach may be used for standoff sensors; however, the concentration map result must be integrated for the particular standoff sensor field of view. The correlation is essentially a scaled covariance calculation between the input sensor data and the SNA tomography output. A histogram of the correlations for all sensors, as shown in the example in Figure 7, can be used to check the overall consistency of the threat map solution. This correlation test check can be used to detect bad sensor data (i.e., the case when a sensor does not correlate with the recent sequence of map solutions, yet most other sensors do correlate well) or bad consensus map results (i.e., the case when most sensors don’t correlate with the map results). The results of consistency checking are fed back to the input data preprocessing as shown in the design of Figure 1. The purpose of the feedback is to either reject or adjust (e.g., apply a corrective offset) a particular input data stream from a particular sensor.

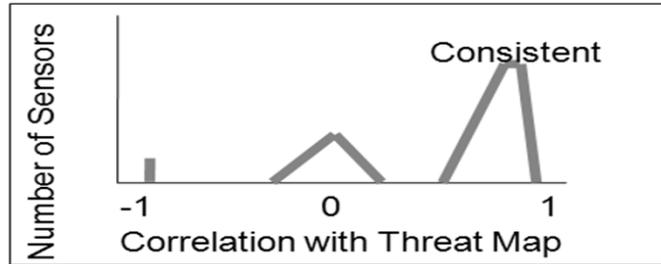


Figure 7. The concept of comparing individual sensor responses against the consensus map answer as a histogram of correlation coefficients is shown. It is assumed that a few bad sensors are not influential enough to grossly skew the consensus map.

5. SNA DATA PRODUCTS FOR THE COMMON OPERATING PICTURE (COP)

Concentration maps are overkill for many military COP display needs; however, the tomography concentration map results are necessary for consistency checking as discussed in section 4. Quantitative data from multiple sensors should converge on the same concentration map result if the data are consistent. A concentration map result can always be degraded to a simpler format such as agent ID, agent class, and 2D cloud boundary polygon coordinates before the result is sent on to a COP map display. A desired threshold level, e.g., concentration + uncertainty > immediate danger to life and health (IDLH) concentration, may be used to define the threat cloud boundary.

6. SIMULATION BASED DEVELOPMENT PLANS FOR SENSOR NETTING ALGORITHMS

Our approach to SNA development is to build a simulation environment where all system parameters can be controlled and manipulated. In this environment, the threat data flow from a simple cloud model, to a network of sensor sampling models (for both point and standoff types), to a SNA processing node, and finally to a fused common operating picture (COP). Additionally, a separate COP will simultaneously show raw un-fused sensor data so that the difference between fused and un-fused data can be visualized. This simulation concept is shown in Figure 8, which is made from actual screen shots taken from a real simulation run. These screen shots include the main software programs used for the SNA test environment:

- Virtual Instrument Response Generator (VIRG) is a program for creating a simulated threat cloud(s) as a function of time. VIRG generates input data for each sensor model client that is connected over the network. The VIRG output depends on parameters provided by the sensor model, such as type (point or standoff), integration time, field of view (for standoff sensors), etc.
- Sensor model is a Labview program that can simulate a point or a standoff sensor. The user can select noise, bias error, integration time, data rate, and FOR scan pattern (for standoff sensors only). A user adjustable Markov process within the sensor model is used to add noise (and false alarms) to the input data stream received from VIRG.
- Un-fused COP display, showing all recent point and standoff vectors overlaid on a map
- SNA with fused COP display, showing threat map results (via Google Earth using KML files)

This environment will be used to test and refine the SNA during the phase II SBIR effort.

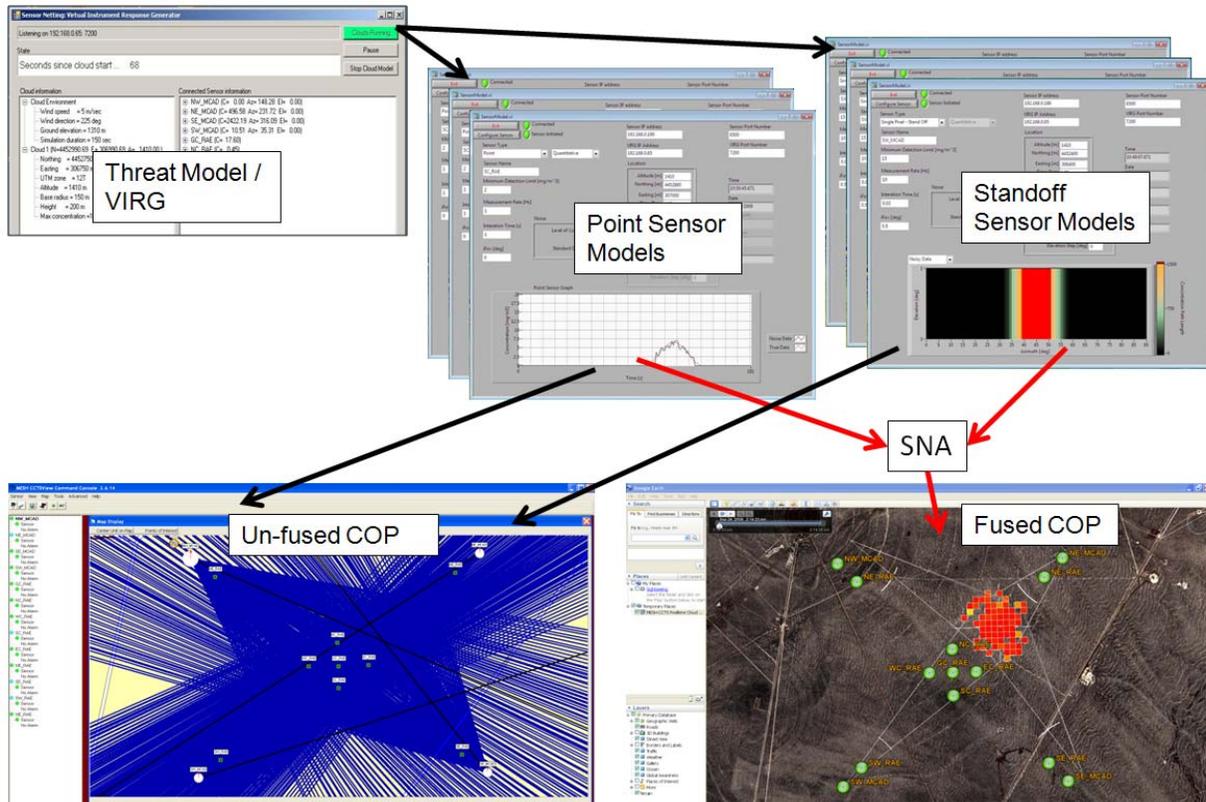


Figure 8. The simulation environment is shown including VIRG (threat model and data source for sensors), sensor models (including simulated point and standoff sensors), a SNA node for fusing the data, a fused COP, and an un-fused COP.

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