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Performance-Driven Resource Management In Layered Sensing

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Abstract - Layered sensing provides a hierarchical net-centric architecture for universal situational awareness with global coverage and persistent surveillance. Sensors in the layered hierarchy provide spatial, temporal, spectral, and polarization diversity with different scales and resolutions over different time horizons. Cooperative management of netted sensors is a successful strategy to achieve targeting performance and overall measures of merit (MOM) goals. After a brief introduction to issues in layered sensors, a resource management strategy based on geometry information is described so as to enhance performance in target detection (minimum detectable Doppler) and tracking accuracy (geometric dilution of precision). Preliminary simulation results are presented to illustrate this Geometric Approach to Layered Sensing (GALS) concept.

Keywords: Layered Sensing, Performance-Driven, Geometric Approach, Resource Management, Measures of Merit (MOM)

1 Layered Sensing

Layered sensing is aimed at providing universal situational awareness with global coverage and persistent surveillance [2, 15]. A scenario of layered sensing is shown in Fig. 1 [9] wherein high altitude platforms afford target detection, unmanned aerial vehicles (UAV) maintain area surveillance for target tracking, and ground sensors can provide individual audio reports for target identification.

For such a layered sensing scenario, the need for intelligent sensor management (SM) is illustrated via the simple space-time diagram in Fig. 2 wherein layered assets are coordinated to achieve mission success. As shown, high altitude platforms such as space-based radar (SBR) in the top layer have wide ground swath sweeping along the orbit for global coverage. Although the satellite ground track repeats regularly, it only offers short time windows on targets during each revisit. Although a fully populated constellation of fast moving low-earth orbit (LEO) satellites can minimize temporal and spatial gaps in ground coverage, a long revisit interval is not effective in tracking of mobile targets. With early detections from the top layer, UAVs in the middle layer can be dispatched and routed to the areas of interest (AOI) for surveillance and tracking. In the bottom layer, ground sensors can stay in the same area so long as the battery lasts but typically have limited spatial coverage.

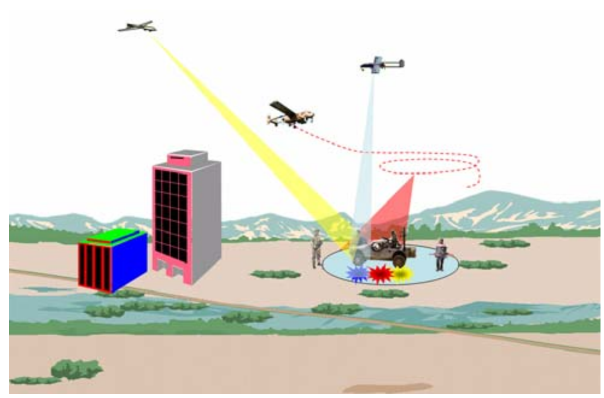

Fig. 1 A Layered Sensing Scenario [9]

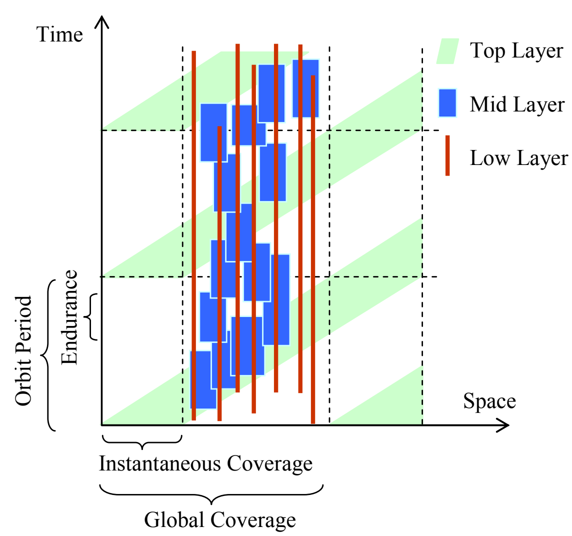

Fig. 2 Space-Time Coverage by Sensors in Different Layers

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14. ABSTRACT

Layered sensing provides a hierarchical netcentric architecture for universal situational awareness with global coverage and persistent surveillance. Sensors in the layered hierarchy provide spatial, temporal, spectral, and polarization diversity with different scales and resolutions over different time horizons. Cooperative management of netted sensors is a successful strategy to achieve targeting performance and overall measures of merit (MOM) goals. After a brief introduction to issues in layered sensors, a resource management strategy based on geometry information is described so as to enhance performance in target detection (minimum detectable Doppler) and tracking accuracy (geometric dilution of precision). Preliminary simulation results are presented to illustrate this Geometric Approach to Layered Sensing (GALS) concept.

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Provided by the high altitude layer, a long list of detections may contain both targets and clutter (false detections). Confirmed detections from lower layers can reduce the position uncertainty estimates; however, unconfirmed detections in the list have rather poor accuracy in their position estimates. This increases the complexity of sensor management and particularly for sensors in the middle layer, which now need to acquire (both search and detect) designated targets prior to tracking, albeit in a much reduced volume.

Resources in layered sensing include both sensing assets and communications assets. This paper will focus on sensors. Sensor management traditionally considers two main themes: (1) *sensor assignment* decides which sensor combination will be assigned to which target over which area and (2) *sensor scheduling* determines when and which sensor will take what action [1, 3, 4, 5, 9, 11, 12, 13]. In layered sensing, however, sensor coordination and data exchange via both wireless and wired network communications play a pivotal role in net centric-operation and interaction, which may involve airborne replays and communications satellites.

Functionality per layer and their interaction are shown on the right hand side of Fig. 3 where information flows from the top layer through the middle layer to the bottom layer and back to the top and middle layers in a closed-loop fashion. Early and quick information (coarse and incomplete) from top layers guide the deployment and execution of lower layers while detailed information derived from lower layers may request special sensor modes of upper layers when flying over special areas to revisit.

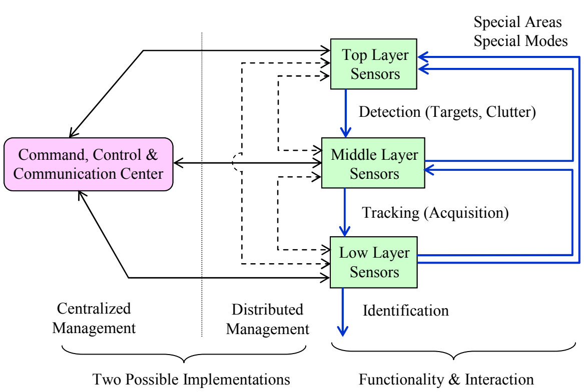


Fig. 3 Implementation Schemes for Layered Functionalities and Interactions

Two possible implementation schemes of the desired interactions are shown on the left hand side of Fig. 3. One is the *centralized management* scheme where sensors in all layers go through the command, control, and communication (C3) center. The other scheme is *distributed (decentralized) management* where sensors in different layers communicate to one another directly. Data link bandwidth, latency, and reliability are key issues in net-centric sensing.

A special aspect of sensor coordination is target handover/cueing, which occurs between layers and within the same layer. One example is correlation of tracks from sensors that lack simultaneous coverage [6]. The cueing from a wide field of view (FOV) sensor to a narrow FOV sensor, either co-located or remotely, is another example. Similarly, handover of targets to a guided weapon from its launch platform is a third example. Proper inter-layer and intra-layer transitions are required to ensure coverage continuity in both time and space. However, transition in layered sensing is more complicated simply because of a large number of detections with large uncertainty in addition to severe constraints on the part of sensors and communication links available in time and space for needed coverage. It becomes clear that efficient resource management becomes indispensable.

The rest of the paper is organized as follows. In Section 2, the resource management strategy based on geometry information is described with two illustrating examples. One example is to enhance tracking accuracy in terms of geometric dilution of precision (GDOP) while the other is to enhance target detection performance with relative target-sensor velocity above the minimum detectable velocity (MDV). Finally, the paper is concluded in Section 3.

2 Geometric Approach to Layered Sensing (GALS)

Layered sensing is a multi-sensor multi-target environment wherein a performance-driven strategy is aimed at obtaining the best targeting results possible via clever use of available resources. The resource management therefore assumes the responsibility of sensor assignment, sensor scheduling, sensor data exchange, and sensor data fusion. For cooperative distributed sensors, they can act together via communication links to improve detection probability, success of classification, tracking accuracy, and the respective rates. Two examples of the geometric approach to layered sensing (GALS) are presented below.

Example 1: Geometric Dilution of Precision (GDOP) as MOM

Depending on the overlapping of multiple sensors in time, space, spectrum, and polarization, the resource manager may assign a sensor to multiple targets or have a target covered by multiple sensors. There are several criteria that can be used to conduct sensor-to-target assignment. One is to ensure persistent tracking of the target as it roams around, that is, to have maximum temporal and spatial coverage. Another is to ensure maximum target detection. At least two factors affect the probability of detection, one is the distance from the sensor to target (the reflected signal power is inversely proportional to R^4 where R is the range from an active sensor to the target) and the other is the relative velocity vector. In the latter case, both target and sensor velocity vectors are utilized in the assignment process, which will be discussed in the second example.

A criterion for maximum accuracy is presented in the following example. Active ranging sensors or passive bearing-only sensors utilize multiple measurements to determine a target's position. Measurements at different locations can be obtained from distributed sensors or from the same sensor but at different time instants over which either the target or sensor or both have meaningfully moved.

Positioning performance can be estimated from using nonlinear (range or bearing or both) measurements. Analogous to the methods used in [8], assume that the target is at $\mathbf{x}$ and the i-th sensor is at $\mathbf{x}_i$. The i-th sensor's measurement is given by:

$$z_i = f_i(\mathbf{x}, \mathbf{x}_i) + v_i \tag{1}$$

where $f_i(\cdot,\cdot)$ is a nonlinear measurement equation and v_i is the sensor measurement error being zero-mean Gaussian $\mathcal{N}(0, \sigma_i^2)$.

With an initial estimate of the target position denoted by $\mathbf{x}_0$, the nonlinear range measurement can be written as:

$$z_i = f_i(\mathbf{x}_0, \mathbf{x}_i) + \mathbf{h}_i^T(\mathbf{x} - \mathbf{x}_0) + v_i \tag{2a}$$

$$\mathbf{h}_i^T = \begin{bmatrix} \frac{\partial z_i}{\partial x_1} & \frac{\partial z_i}{\partial x_2} & \cdots & \frac{\partial z_i}{\partial x_n} \end{bmatrix} \tag{2b}$$

The equation can be further written as:

$$\tilde{z}_i = z_i - f_i(\mathbf{x}_0, \mathbf{x}_i) + \mathbf{h}_i^T \mathbf{x}_0 = \mathbf{h}_i^T \mathbf{x} + v_i \tag{3a}$$

$$\tilde{\mathbf{z}} = \mathbf{H}\mathbf{x} + \mathbf{v} \tag{3b}$$

$$\tilde{\mathbf{z}}^T = \begin{bmatrix} \tilde{z}_1 & \tilde{z}_2 & \cdots & \tilde{z}_n \end{bmatrix} \tag{3c}$$

$$\mathbf{v}^T = \begin{bmatrix} v_1 & v_2 & \cdots & v_n \end{bmatrix} \tag{3d}$$

$$\mathbf{H}^T = \begin{bmatrix} \mathbf{h}_1 & \cdots & \mathbf{h}_m \end{bmatrix} \tag{3e}$$

The least square solution is given by:

$$\hat{\mathbf{x}} = (\mathbf{H}^T \mathbf{R}^{-1} \mathbf{H})^{-1} \mathbf{H}^T \mathbf{R}^{-1} \tilde{z} \tag{4a}$$

$$\mathbf{P} = E\{(\mathbf{x} - \hat{\mathbf{x}})^T (\mathbf{x} - \hat{\mathbf{x}})\} = (\mathbf{H}^T \mathbf{R}^{-1} \mathbf{H})^{-1} \tag{4b}$$

Assume that all sensors have the same quality with $\mathbf{R} = \sigma^2 \mathbf{I}$. The solution is then determined by the linearization matrix $\mathbf{H}$. A scalar value that characterizes the solution is the geometrical dilution of precision (GDOP) defined as:

$$\mathrm{GDOP} = \sqrt{\mathrm{trace}((\mathbf{H}^T \mathbf{R}^{-1} \mathbf{H})^{-1})} \tag{5a}$$

$$= \sqrt{\mathrm{trace}((\mathbf{H}^T \mathbf{H})^{-1})} \text{ when } \mathbf{R} = \mathbf{I} \tag{5b}$$

where trace$(\cdot)$ stands for the trace of a matrix.

Consider an active sensor with ranging measurements in a two dimensional case as shown in Fig. 4. The nonlinear range equation and its linearization are:

$$f_i(\mathbf{x}, \mathbf{x}_i) = r_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{6a}$$

$$\mathbf{h}_i = \begin{bmatrix} \frac{x_0 - x_i}{r_i} \\ \frac{y_0 - y_i}{r_i} \end{bmatrix} = \begin{bmatrix} \cos(\theta_i) \\ \sin(\theta_i) \end{bmatrix} = \mathbf{e}_i \tag{6b}$$

It is clear from (6b) that $\mathbf{h}_i$ is the line of sight vector from the i-th sensor to the target, denoted by $\mathbf{e}_i$. As a result, the GDOP is only determined by the geometry (angular relationship), not by the actual separation (distance) for active sensors. The thermal noise does not depend on the sensor to target range but the target echo strength does. So does the resulting signal to noise ratio (SNR) and this will affect the equivalent measurement covariance matrix $\mathbf{R}$. This has significant ramifications in geometry-based sensor assignment and scheduling.

Assume the measurement matrix $\mathbf{H}$ is a non-singular square matrix (a very restrictive example) and $\mathbf{R}$ is a diagonal matrix with unequal diagonal elements σ_i^2, which is a function of SNR. Then,

$$\begin{aligned} &(\mathbf{H}^T \mathbf{R}^{-1} \mathbf{H})^{-1} = \mathbf{H}^{-1} \mathbf{R} (\mathbf{H}^T)^{-1} \\ &= \mathrm{trace}(\mathbf{H}^{-1} \mathbf{R} (\mathbf{H}^T)^{-1}) = \mathrm{trace}(\mathbf{R} (\mathbf{H}\mathbf{H}^T)^{-1}) \\ &= \sum_{i=1}^{n} \sigma_i^2 (\mathbf{H}\mathbf{H}^T)_{ii}^{-1} \end{aligned} \tag{7}$$

where the subscript ii stands for the i-th diagonal element of the matrix $(\mathbf{H}\mathbf{H}^T)^{-1}$. Clearly, the contribution of the i-th sensor to the GDOP is weighted by σ_i^2. Similar results for more general cases can be found in [17].

For the case with two ranging sensors, GDOP can be written as:

$$\mathrm{GDOP}_{\mathrm{Range}} = \sqrt{\frac{\sigma_1^2 + \sigma_2^2}{\sin^2(\theta_1 - \theta_2)}} \tag{8a}$$

$$= \begin{cases} \sqrt{\sigma_1^2 + \sigma_2^2}, & |\theta_1 - \theta_2| = \pi/2 \\ \infty, & |\theta_1 - \theta_2| = 0, \pi \end{cases} \tag{8b}$$

$$= \sigma_1 \sqrt{\frac{1 + (\sigma_2/\sigma_1)^2}{\sin^2(\theta_1 - \theta_2)}} \tag{8c}$$

$$= \sigma \sqrt{\frac{2}{\sin^2(\theta_1 - \theta_2)}}, \ \sigma_2 = \sigma_1 = \sigma \tag{8d}$$

If we have to choose two out of many (say, three) sensors to form a solution, we need to compare all possible configurations (three pairs in this case, namely, Sensors {1 and 2}, {1 and 3}, and {2 and 3}) in terms of their GDOP as a function of the sensor quality (σ_2/σ_1) and their relative position ($\theta_1 - \theta_1$) assuming all other factors are equal.

Assume that Sensor 1 has the smallest measurement error and is chosen as the reference. Assume Sensor 2 is of the same quality as Sensor 1 ($\sigma_2/\sigma_1 = 1$) but it makes 40° with respect to Sensor 1 ($\theta_2 - \theta_1 = 40°$). Although Sensor 3 has the best geometry relative to Sensor 1 with $\theta_3 - \theta_1 = 90°$, it

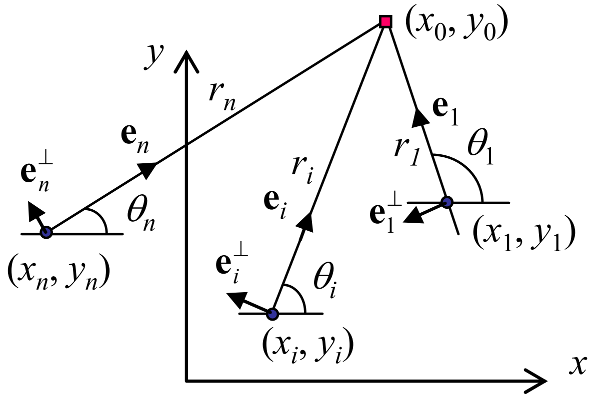


Fig. 4 GDOP for Ranging and Bearing-Only Sensors

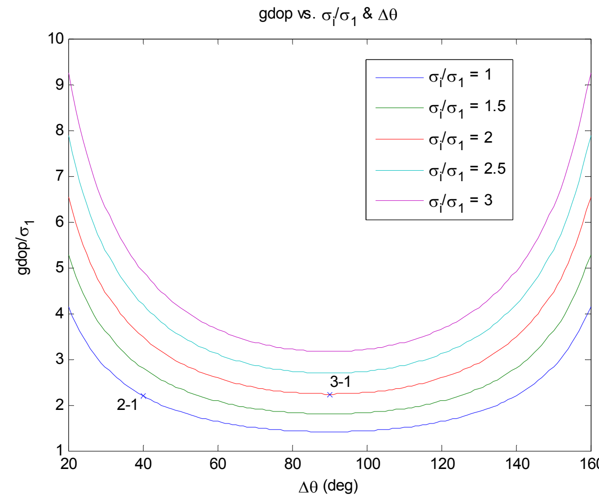


Fig. 5 Optimal Selection of Sensor Pairs

has the worst quality with $\sigma_3/\sigma_1 = 2$. The resulting GDOP for the pair 1 and 2 is $\text{GDOP}_{1,2} = 2.20$ while it is $\text{GDOP}_{1,3} = 2.24$ for the pair {1 and 3}. The optimal choice is therefore the pair {1 and 2}, as shown in Fig. 5.

Referring to Fig. 4 again, we now consider a passive sensor with bearing measurements in a two dimensional case. The nonlinear angular equation and its linearization are:

$$f_i(\mathbf{x}, \mathbf{x}_i) = \theta_i = \tan^{-1}\left(\frac{y - y_i}{x - x_i}\right) \tag{9a}$$

$$\mathbf{h}_i = \begin{bmatrix} -\dfrac{y_0 - y_i}{r_i^2} \\ \dfrac{x_0 - x_i}{r_i^2} \end{bmatrix} = \begin{bmatrix} \dfrac{-\sin(\theta_i)}{r_i} \\ \dfrac{\cos(\theta_i)}{r_i} \end{bmatrix} = \frac{1}{r_i}\begin{bmatrix} -\sin(\theta_i) \\ \cos(\theta_i) \end{bmatrix} = \frac{\mathbf{e}_i^{\perp}}{r_i} \tag{9b}$$

Comparing (9b) to (6b) shows that the measurement matrix $\mathbf{h}_i$ for the bearing-only sensor is range-dependent and it is in fact perpendicular to the line of sight vector from sensor to target. When the range-dependence and angular errors are combined in the GDOP (5), it provides a position error perpendicular to the LOS (or along $\mathbf{e}_i^{\perp}$), that is, $r_i\sigma_i$.

For the case with two bearing-only sensors, GDOP of (5) can be written as:

$$\text{GDOP}_{\text{Bearing}} = \sqrt{\frac{r_1^2\sigma_1^2 + r_2^2\sigma_2^2}{\sin^2(\theta_1 - \theta_2)}} \tag{10a}$$

$$= \begin{cases} \sqrt{r_1^2\sigma_1^2 + r_2^2\sigma_2^2}, & |\theta_1 - \theta_2| = \pi/2 \\ \infty, & |\theta_1 - \theta_2| = 0, \pi \end{cases} \tag{10b}$$

$$= r_1^2\sigma_1^2\sqrt{\frac{1 + (r_1\sigma_1 / r_1\sigma_1)^2}{\sin^2(\theta_1 - \theta_2)}} \tag{10c}$$

$$\text{GDOPN}_{\text{Bearing}} = \sqrt{\frac{1}{\sigma_R^2}\frac{r_1^2\sigma_1^2 + r_2^2\sigma_2^2}{\sin^2(\theta_1 - \theta_2)}} \tag{10d}$$

$$= \sqrt{\frac{2}{\sin^2(\theta_1 - \theta_2)}} \tag{10e}$$

$$= \begin{cases} \sqrt{2}, & |\theta_1 - \theta_2| = \pi/2 \\ \infty, & |\theta_1 - \theta_2| = 0, \pi \end{cases}, \text{ for } \sigma_2 = \sigma_1 = 1, \text{ and } r_1 = r_2 \tag{10f}$$

The same results for ranging sensors can be applied to bearing-only sensors when the cross range error $r_i(\sigma_i)_{\text{bearing}}$ used in (10) is treated in much the same way as the ranging error $(\sigma_i)_{\text{ranging}}$ in (8b). The performance curve for sensor pair selection as shown in Fig. 2 is also applicable.

To emphasize the geometric aspect, a normalized GDOP or GDOPN was introduced in [8]. It is defined as:

$$\text{GDOPN} = \sqrt{\frac{\text{trace}((\mathbf{H}^T\mathbf{R}^{-1}\mathbf{H})^{-1})}{\sigma_R^2}} \tag{11a}$$

where σ_R^2 is an averaged noise variance defined as:

$$\sigma_R^2 = \frac{1}{N}\sum_{i=1}^{N} r_i^2\sigma_i^2 \tag{11b}$$

Indeed, the original definition assumes $\mathbf{R} = \mathbf{I}$ and GDOP is related purely to the geometry. This works well for such applications as GPS satellites selection above a certain elevation mask angle. For a near Earth user, its ranges to most satellites are about the same and the SNR does not vary greatly. As a result, GDOP is a good choice. However, the difference in distance to targets from sensors in various layers may be significant and so is their SNR. By consequence, the use of GDOP weighted with measurement quality seems to be more useful as illustrated in Fig. 5.

The GDOP definitions above involve the measurement matrix $\mathbf{H}$ and the product of its transpose $\mathbf{H}^T$. This is similar to the Fisher information gain and is also related to the Cramer-Rao lower bound. It is of interest to further investigate their relationships.

A practical problem with the least squares solution (4) is the inability to inverse the matrix term $\mathbf{H}^T\mathbf{RH}$. This matrix inverse problem occurs when the vectors of the observation matrix $\mathbf{H}$ become collinear (rank-deficient), which produces unstable estimates. Under this condition, the GDOP is excessively high.

However, the matrix inverse constraint condition may be used explicitly for sensor assignment. When it happens, one could task another available sensor with near optimum geometry. However, when there is no time to displace the sensors to the desired locations, temporary means may be applied to ensure the quality of solution. One technique is to apply the *ridge regression* (regularized least squares, constrained least squares, or Tikhonov regularization) in the interim before the optimal displacement is achieved.

Ridge regression attempts to limit the minimum values of the diagonal values of $\mathbf{H}^T\mathbf{H}$ by replacing it with $\mathbf{H}^T\mathbf{H} + \kappa\mathbf{I}$ in (4a) [7, 10]. It is used to reduce the overall mean squared errors and the variance inflated by poor GDOP at the expense of higher bias. Explicitly, the ridge regression is written as:

$$\hat{\mathbf{x}} = (\mathbf{H}^T\mathbf{R}^{-1}\mathbf{H} + \kappa\mathbf{I})^{-1}\mathbf{H}^T\mathbf{R}^{-1}\tilde{\mathbf{z}} \tag{12a}$$

$$\mathbf{P} = (\mathbf{H}^T\mathbf{R}^{-1}\mathbf{H} + \kappa\mathbf{I})^{-1} \tag{12b}$$

This can be viewed as the optimal solution that minimizes the following performance index:

$$J = (\tilde{\mathbf{z}} - \mathbf{Hx})^T\mathbf{R}^{-1}(\tilde{\mathbf{z}} - \mathbf{Hx}) + \kappa\mathbf{x}^T\mathbf{x} \tag{13}$$

It contains a measurement error term and a constraint term on the solution. Such a formulation is also referred to the regularized least squares (RLS) [14]. It is also similar to the nonlinear constrained optimization used for track to road fusion [16].

Example 2: Relative Motion for Detection in Clutter

One task of sensor management is to put the right sensors in the right places at the right times and doing the right processing. The goal of the four "rights" is to improve target detection probability and state estimation accuracy yet with minimum efforts (cost and time).

With advance in netted sensors and multi-input and multi-output (MIMO) radar, distributed sensors may be coordinated to produce better fusion results. Clearly there are two lower levels of fusion, namely, *detection* or *feature fusion* (classifier fusion) and coordinated processing and *signal fusion* (coherent and non-coherent integration). One example of signal fusion is in a bistatic setting where two radars look at the same place, one serves as the transmitter and the other as receiver. The backscattered signal at the transmitter may be combined with the forward-scattered signal at the receiver, coherently or non-coherently, to enhance the detection. This may require one radar sending its received signal (translated onto a different frequency) to the other radar. Large bandwidth is required for communication but only at those critical moments for high-valued targets. Bistatic detection becomes more viable when there are more receivers in the network dwelling at the same region of interest where both signal fusion and classifier fusion can take place.

In addition to the two types of sensors discussed in the last section, namely, (1) passive sensors with bearing-only measurements and (2) active sensors with range measurements (no or poor angular measurements), we now consider measurements that depend on relative velocity along the line of sight (LOS) direction to targets. An example is an airborne ground moving target indicator (GMTI).

As analyzed in the last section, the relative geometry affects target detection and estimation accuracy. This is illustrated again in Fig. 6. In Fig. 6(a) for passive sensors with bearing-only measurements, the positioning accuracy depends not only on the sensors' accuracy measurement quality and the range to target but also on the relative geometry of the sensors to target. Fig. 6(b) shows active sensors with range measurements. Its positioning accuracy depends on the sensors' accuracy measurement quality as well as on the relative geometry of the sensors to target. The dependence on the range-to-target is due to SNR (partially reflected in the range measurement errors).

For the third type of measurements, consider the encounter geometry shown in Fig. 8 where the range rates due to the target motion are given by:

$$\dot{r}_1^t = V_t \sin(\theta_1) \tag{14a}$$

$$\dot{r}_2^t = V_t \sin(\theta_1 + \theta_2) \tag{14b}$$

where V_t is the target's velocity and θ_1 and θ_2 are the viewing angles of the two sensors relative to the target's broadside, respectively.

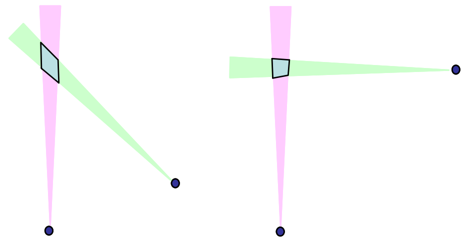
The range rates in (14a) and (14b) specify the Doppler frequency as seen by individual sensors when they operate in a monostatic manner (for two-way propagation, a factor of two is omitted). In the bistatic setting, the Doppler frequency is then given by:

$$\begin{aligned}\dot{r}^t &= V_t \sin(\theta_1) + V_t \sin(\theta_1 + \theta_2) \\ &= 2V_t \sin(\theta_1 + \frac{\theta_2}{2})\cos(\frac{\theta_2}{2})\end{aligned} \tag{15}$$

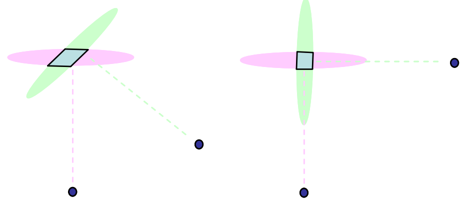
When $\theta_1 = 0$, (15) is identical to (12b), which can be easily verified from Fig. 8. For a given θ_1 of the first sensor, the placement of the second sensor at θ_2 is such that the range rate is maximized. The solution can be written as:

$$\theta_1 + \theta_2 = sign(\sin(\theta_1))\frac{\pi}{2} \tag{16a}$$

$$\theta_2 = sign(\sin(\theta_1))\frac{\pi}{2} - \theta_1 \tag{16b}$$



(a) Passive Bearing-Only Sensors



(b) Active Ranging Sensors

Fig. 6 Geometric Effects on Target Positioning

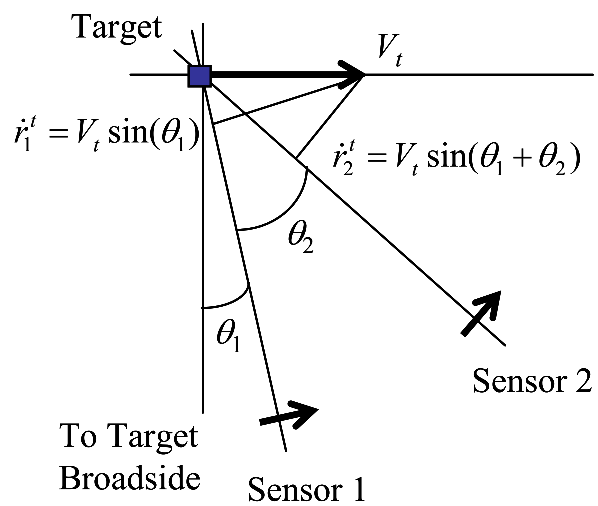


Fig. 7 Two Sensors with a Target

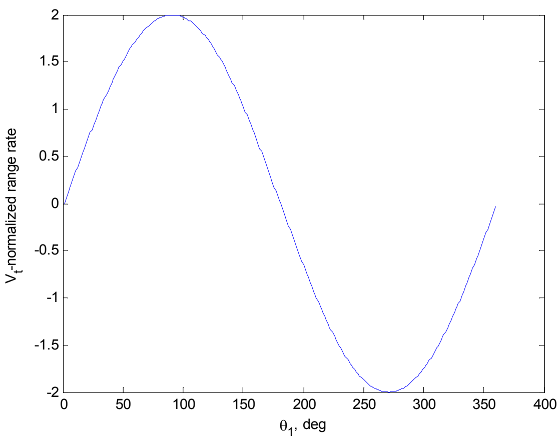


Fig. 8(a) Monostatic at θ_1

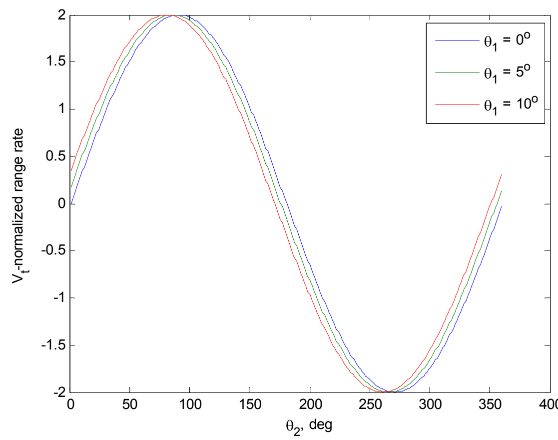


Fig. 8(b) Monostatic at θ_2 As a Function of θ_1

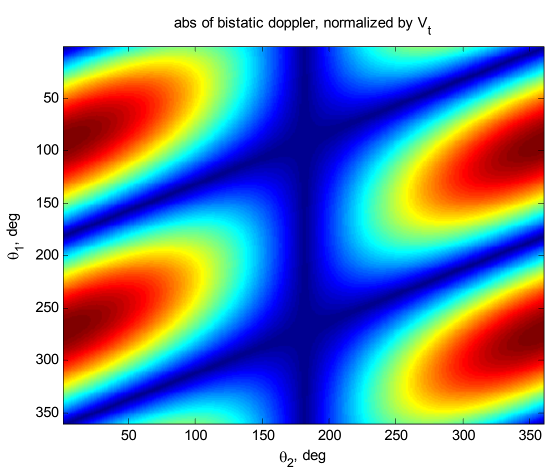


Fig. 9(a) Bistatic with θ_1 vs. θ_2

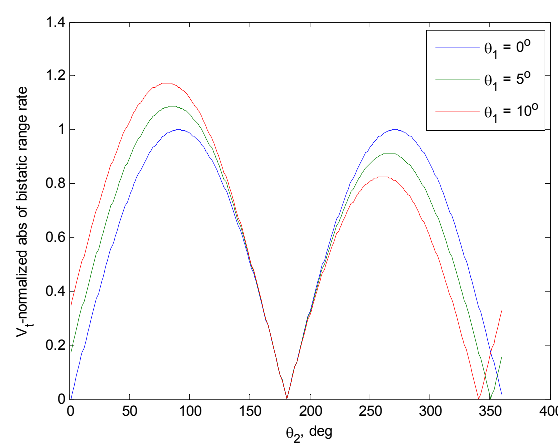


Fig. 9(b) Bistatic as a Function of θ_2 for Selected θ_1

The result in (16b) is significant. For the two types of sensors shown in Figs. 6(a) and 6(b), the angular separation is desired to be 90^o or orthogonal. However, for GMTI type of sensors, the best angular separation is the ninety degrees (90^o) complement of the first sensor's angular position to the target's broadside. That is, to place the second sensor in the direction of the target' velocity.

Fig. 8(a) shows (14a), which indicates positive and negative maximum values at $\pm 90^o$, that is, in the same direction or opposite to the target's velocity vector.

Fig. 8 (b) shows (14b) for three values of $\theta_1 = 0^o$, 5^o, and 10^o. The curve is shifted leftward and so is the peak point. This is consistent with (16).

Fig. 9(a) shows the absolute value of (15) as a function of θ_1 and θ_2 where the dark brown color represents the maximum and the dark blue for minimum (zero) values. Fig. 9(b) shows the three rows of Fig. 9(a). Again the best placement of the 2nd sensor is at the peak location and this agrees with (16).

The above results afford several observations for managing mixed sensors. First, if insufficient information is available about the target and its motion (velocity vector), the placement of two sensors 90° apart is a reasonable choice because this produces good GDOP and avoids the worst case Doppler detection. Knowing the target velocity vector or its prediction requires a side-looking sensor to fly over the target's path (perpendicular to it). When additional information is available about one sensor's viewing angle, the placement of a second sensor or more can be made according to (16) so as to improve the overall targeting capability and estimation accuracy.

3 Inter-Layer Transitions[1]

The handoff of target information from one layer to the most appropriate sensors in another layer (i.e., inter-layer transition) is an important aspect of resource management in layered sensing as discussed in Section 1. The two geometric approaches presented in Section 2, namely, using GDOP as MOM and creating relative motion to maximize detection in clutter, can be used to implement an optimal handoff scheme.

The information about a target from one layer may be represented in terms of the target kinematic state estimate (a track) and the estimation error covariance and possibly a target ID and its confidence level. However, some passive sensors may only offer bearings associated with a detection and a level of quality. Given such *a priori* information, which may be predicted forward to a future time or over a time interval, the most appropriate sensors are chosen such that the updated error covariance at that particular future time or over the future time interval is minimized. The GDOP method (or a similar eigen analysis [17]) can be applied for this purpose. However, this GDOP method assumes that the designated target can be found at the future updating time and this involves target detection and detection-to-track association so as to carry out this inter-layer transition. As a result, a viable sensor-to-target assignment approach ought to take a holistic view in which maximum probability of target detection, correct data association, effective position error reduction, and improved target ID are all design goals under such constraints as limited endurance, ECM conditions, adverse environmental factors, and communications [19, 20]. In particular, maximizing target detection and target ID may also involve adaptive waveform selection at the same time as sensor-to-target assignment [21, 22].

In addition, the concept of "target value" can be utilized to prioritize the assignment of sensor functions, which is more operational applicable. In case of too little resource capacity (overload), sensor tasks need to be assigned to the (operationally) most important objects. Assigning values to targets is no easy task. At least three facets can be considered: (1) target ID or class, (2) a target's proximity to tactical positions in the field, and (3) a target's need for sensor updating.

It is therefore necessary to have an idea of the class a target belongs to and to deploy those sensors that can provide such class information (both cooperative and non-cooperative). In fact, taking the target class into account could also help in optimizing the geometric aspects (as shown in Figs. 6 and 7) as it helps to estimate the RCS/ "Swerling case" combination [18], thus yielding a better prediction of the P_d.

Layered sensing involves managing sensors that are spread over a large area. The meteorological effects cannot be overlooked. Two sensors that have similar performance may yield different results against the same target type when the EM propagation path of one of the sensors is affected by ducting effects for instance. These and other issues are made a part of our ongoing investigation.

4 Conclusions

Within the framework of layered sensing, this paper described the needs, issues, and approaches to resource management. In particular, the *geometric approach to layered sensing* (GALS) is detailed to enhance performance in target detection (minimum detectable Doppler) and tracking accuracy (geometric dilution of precision). Simulation examples showed that such a geometrical performance-based layered-sensing approach could be used for sensor management in both sensor selection and sensor scheduling. Ongoing work is focused on cooperative management of netted sensors in a more complex environment to achieve targeting performance and overall mission goals.

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