KUPS: Knowledge-Based Ubiquitous and Persistent Sensor Networks for Threat Assessment

QILIAN LIANG, Senior Member, IEEE
University of Texas at Arlington

XIUZHEN CHENG, Member, IEEE
The George Washington University

We propose a knowledge-based ubiquitous and persistent sensor network (KUPS) for threat assessment, in which "sensor" is a broad characterization. It refers to diverse data or information from ubiquitous and persistent sensor sources such as organic sensors and human intelligence sensors. Our KUPS for threat assessment consists of two major steps: situation awareness using fuzzy logic systems (FLSs) and threat parameter estimation using radar sensor networks (RSNs). Our FLSs combine the linguistic knowledge from different intelligent sensors, and our proposed maximum-likelihood (ML) estimation algorithm performs target radar cross section (RCS) parameter estimation. We also show that our ML estimator is unbiased and the variance of parameter estimation matches the Cramer-Rao lower bound (CRLB) if the radar pulses follow the Swerling II model. Simulations further validate our theoretical results.

Manuscript received August 10, 2006; revised February 28, 2007; released for publication August 20, 2007.

IEEE Log No. T-AES/44/3/929753.

Refereeing of this contribution was handled by J. P. Y. Lee.

The work of Liang was supported by the U.S. Office of Naval Research (ONR) under Grant N00014-07-1-0395 and ONR Young Investigator Program Award under Grant N00014-03-1-0466.

The work of Cheng was supported by the National Science Foundation (NSF) CAREER award under Grant CNS-0347674.

Authors' addresses: Q. Liang, Dept. of Electrical Engineering, University of Texas at Arlington, Arlington, TX 76019-0016, E-mail: (liang@uta.edu); X. Cheng, Dept. of Computer Science, The George Washington University, Washington, D.C. 20052.

I. INTRODUCTION AND MOTIVATION

In current and future military operational environments, such as global war on terrorism (GWOT) and maritime domain awareness (MDA), warfighters require technologies evolved to support information needs regardless of location and consistent with the user's level of command or responsibility and operational situation. To support this need, the U.S. Department of Defense (DoD) has developed the concept of network centric warfare (NCW), defined as "*military operations that exploit state-of-the-art information and networking technology to integrate widely dispersed human decision makers, situational and targeting sensors, and forces and weapons into a highly adaptive, comprehensive system to achieve unprecedented mission effectiveness*" [1].

The DoD has defined three levels of data fusion for NCW. the level 1 data fusion combines data from single or multiple sensors and sources to provide the best estimate of objects and events in the battlespace in terms of their position, kinematics (e.g. tracks), identity, or identification features. In [14], decision fusion rules were studied in multi-hop wireless sensor networks. In [10], a fuzzy logic approach for postdetection signal integration and detection was proposed, and a functional paradigm for fuzzy data fusion was presented in [25]. However, too often in level 1 data fusion, the characteristics of objects that are not of interest will be similar to those of threat objects. The conventional approach to false alarm control is to reduce sensitivity of the radar in areas of clutter, using sensitivity time control (STC) [26]. In [11], we proposed a maximum-likelihood (ML) automatic target recognition (ATR) algorithm using constant frequency (CF) waveform design and diversity, assuming perfect delay and Doppler. In [12], we applied linear frequency modulation (LFM) waveform design and diversity to ATR with delay-Doppler uncertainty. Level 2 data fusion focuses on situation assessment. This requires recognition of objects/entities in the regions of interest, as well as recognizing activities of these objects, and inferring their relationships. Level 3 data fusion is threat assessment, which requires inferring the intent of objects/entities, or groups of objects, in the regions of interest. Higher level data fusion also needs lower level data fusion results. In level 2/3 data fusion, some works have been reported. A situation/threat assessment fusion system was proposed in [3]. Other approaches include multiple attribute decision making [4], Bayesian networks [21], etc. In [6], an intelligent threat assessment processor using genetic algorithms and fuzzy logic was proposed. In [20], threat assessment was studied in tactical airborne environments. In [9], neural network was applied to threat assessment for automated visual surveillance.

In [5], an intelligent assistant to provide automatic situation and threat advice in the Air Defence Ground Environment was proposed. In [2], a situation and threat assessment model based on group analysis was studied.

Despite these above advances, current shortfalls in warfighting functionality result from limitations in technology. For example, accurate and timely information about battlespace objects and events is not available to support warfighter decision making (including reliable location, tracking, combat identification, and targeting information). While massive amounts of data will be generated by penetrating persistent sensors, warfighters require technologies that not only integrate information from diverse sources but also provide indications of information significance in ways that support the user's tactical decision needs regardless of location and are consistent with the user's level of command or responsibility and operational situation. Assuming the availability of object track and identity information, automated decision tools that transform this information into actionable knowledge for the decision maker are required. The tools and technologies to resolve these shortfalls must address data fusion, particularly at levels 2/3 [1]. In this paper, we propose a knowledge-based ubiquitous and persistent sensor network (KUPS) for threat assessment.

The rest of this paper is organized as follows. In Section II, we introduce the new concept of KUPS, and in Section III, we propose knowledge-based situation awareness using intelligence (INT) sensors. In Section IV, we propose a fine target recognition and threat assessment scheme that employs an ML estimation algorithm for threat target radar cross section (RCS) parameter estimation using radar sensor networks (RSNs). Finally, we conclude this paper and discuss future research directions in Section V.

II. INTRODUCTION TO KNOWLEDGE-BASED UBIQUITOUS AND PERSISTENT SENSOR NETWORKS: A NEW CONCEPT

In this paper, we propose an NCW model entitled knowledge-based ubiquitous and persistent sensor network (KUPS), in which "sensor" is a broad characterization concept. It means ubiquitous and persistent sensors sources such as the following.

1) Organic sensors (e.g., radar, electro-optic and infrared, acoustic, and nonacoustic) deployed on air, ground, surface, or unattended platforms.

2) Signal intelligence (SIGINT) including electronic intelligence (ELINT) and communication intelligence (COMINT). For example, it can assign meaningful metadata to each collection, and the metadata is the standardized characterization of data providing descriptors (such as stability, activity, membership, or structure).

3) Human intelligence (HUMINT), e.g., to identify specific people/cells/groups and relationships.

4) Measurement and signatures intelligence (MASINT), e.g., to provide specific weapon system identifications, chemical compositions and material content.

5) Imagery intelligence (IMINT), e.g., to track vehicles through urban area.

6) Open source intelligence (OSINT), e.g., to provide text data collection.

All these sources of information need to be integrated via "sensor networking" to accomplish a mission. In this paper, we apply KUPS to threat assessment, and the organic sensors we use are pulse Doppler radars.

Our KUPS for threat assessment is a hierarchical and recursive architecture which consists of two major steps.

Step 1, Situation Awareness: Performing knowledge-based situation awareness using INT sensors (e.g. SIGINT, HUMINT sensors). Fuzzy rules are used to represent the linguistic knowledge uncertainties from HUMINT sensors, and fuzzy logic systems (FLSs) are used to perform knowledge-based decision making on situation awareness (e.g., threat or nonthreat). If it is assessed as a nonthreat, stops; if it is assessed as a potential threat to issue an indication & warning (I&W), then go to Step 2 for further target recognition and threat assessment.

Step 2, Fine Target Recognition and Threat Assessment: Performing target RCS value estimation using RSNs. We propose an ML estimation algorithm to estimate target RCS parameter value using RSNs. Based on the estimated RCS parameter, the KUPS will advise what kind of target this threat is. The ML estimation algorithm can help to estimate the RCS parameter θ (parameter in a Rayleigh distribution for fluctuating target). However, the same RCS parameters may mean different targets, threats or nonthreats. For example, for $\theta = 2$, the target can be a small flighter aircraft, a small pleasure boat, a bicycle [26], or any other similar size target. This example illustrates that RCS-based level 1 data fusion (e.g., [11, 12]) without considering other context such as geographical information (from OSINT) has very clear disadvantages. So we have to use Step 1 to make the decision first, and only an I&W requires further classification for further action. Sometimes it may be a false alarm based on fine target recongition, therefore Step 2 will make final threat assessment.

Step 2 results can be feedback to Step 1 recursively to further tune the parameters in FLS design. Fig. 1 depicts the relationship between Steps 1 and 2. We discuss these two steps in the following sections.

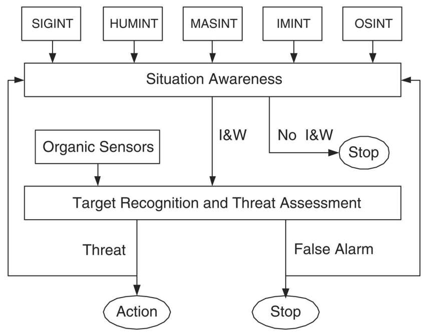


Fig. 1. Relations of Steps 1 and 2.

III. KNOWLEDGE-BASED SITUATION AWARENESS USING INT SENSORS

In knowledge-based situation assessment using INT sensors, fuzzy rules are used to represent the linguistic and numerical knowledge uncertainties from INT sensors, and FLSs are used to perform knowledge-based decision making on threat assessment. We give a brief introduction on FLSs first.

A. Overview of Fuzzy Logic Systems

In general, an FLS is a nonlinear mapping of an input data (feature) vector to a scalar output [16]. Fig. 2 shows the structure of an FLS [16]. When an input is provided to an FLS, the inference engine computes the output set corresponding to each rule. The defuzzifier then computes a crisp output from these rule output sets. Consider a p-input 1-output FLS, using singleton fuzzification, center-of-sets defuzzification [18, 16], and "IF-THEN" rules of the form

$$R^l: \text{ IF } x_1 \text{ is } \mathrm{F}_1^l \text{ and } x_2 \text{ is } \mathrm{F}_2^l \text{ and } \cdots$$
$$\text{and } x_p \text{ is } \mathrm{F}_p^l, \text{ THEN } y \text{ is } \mathrm{G}^l.$$

Assuming singleton fuzzification, when an input $\mathbf{x}' = \{x_1', \ldots, x_p'\}$ is applied, the degree of firing corresponding to the lth rule is computed as

$$\mu_{\mathrm{F}_1^l}(x_1') \star \mu_{\mathrm{F}_2^l}(x_2') \star \cdots \star \mu_{\mathrm{F}_p^l}(x_p') = \mathcal{T}_{i=1}^{p} \mu_{\mathrm{F}_i^l}(x_i') \qquad (1)$$

where $\star$ and $\mathcal{T}$ both indicate the chosen t-norm (minimum or product operation) [16], and $\mu_{\mathrm{F}_i^l}(x_i')$ is the membership grade of fuzzy set F_i^l for input x_i'. There are many kinds of defuzzifiers [16, 18]. In this paper, we focus, for illustrative purpose, on the center-of-sets defuzzifier [18]. It computes a crisp output for the FLS by first computing the centroid c_{G^l} of every consequent set G^l, and then computing a weighted average of these centroids. The weight corresponding to the lth rule consequent centroid is the degree of firing (firing strength) associated with the lth rule, $\mathcal{T}_{i=1}^{p} \mu_{\mathrm{F}_i^l}(x_i')$, so that

$$y_{\cos}(\mathbf{x}') = \frac{\sum_{l=1}^{M} c_{\mathrm{G}^l} \mathcal{T}_{i=1}^{p} \mu_{\mathrm{F}_i^l}(x_i')}{\sum_{l=1}^{M} \mathcal{T}_{i=1}^{p} \mu_{\mathrm{F}_i^l}(x_i')} \qquad (2)$$

where M is the number of rules in the FLS. Readers can refer to [16, 18] for details on FLS. Reference [16] provides a very good tutorial on FLS, and [18] gives an introduction to and directions on FLS development [18].

B. Knowledge-Based Situation Awareness using FLSs

In our FLS design for situation awareness, we consider the following knowledge-based antecedents.

1) The first antecedent is the number of switches from the nonmaneuvering set (constant behavior in speed, acceleration, and direction, etc.) to the maneuvering set (varying behavior in speed, acceleration, and direction, etc). When a target is beginning a maneuver from a nonmaneuvering class, the tracking system can switch the algorithms applied to the problem from a nonmaneuvering set to the maneuvering set. The errors in distance from where the tracker estimates the position of a target between the actual position can be very large when the incorrect motion models are applied to the problem. Additionally, when the tracker does finally catch up to the target after the maneuver, the track will "jump" across the operator's scope giving a very unrealistic and unreliable picture of what that target is actually doing. So a threat target will quite often switch from a nonmaneuvering set to the maneuvering set, and vice versa, to avoid being tracked all the time. This knowledge can be used as an antecedent for situation awareness.

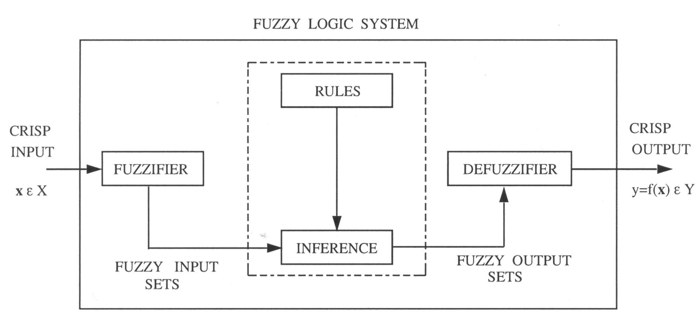


Fig. 2. Structure of FLS.

TABLE I
Fuzzy Rules used in KUPS

Rule #	Ante 1	Ante 2	Ante 3	Consequent
1	low	low	low	weak
2	low	low	moderate	medium
3	low	low	high	strong
4	low	moderate	low	very weak
5	low	moderate	moderate	weak
6	low	moderate	high	medium
7	low	high	low	very weak
8	low	high	moderate	weak
9	low	high	high	medium
10	moderate	low	low	medium
11	moderate	low	moderate	strong
12	moderate	low	high	very strong
13	moderate	moderate	low	weak
14	moderate	moderate	moderate	medium
15	moderate	moderate	high	strong
16	moderate	high	low	very weak
17	moderate	high	moderate	weak
18	moderate	high	high	medium
19	high	low	low	medium
20	high	low	moderate	strong
21	high	low	high	very strong
22	high	moderate	low	weak
23	high	moderate	moderate	medium
24	high	moderate	high	strong
25	high	high	low	very weak
26	high	high	moderate	weak
27	high	high	high	Moderate

Note: Ante 1 is number of switches from nonmaneuvering set to maneuvering set or vice versa. Ante 2 is frequency of appearance of such type of target. Ante 3 is importance of geolocation of target. Consequent is the possibility that target is a threat.

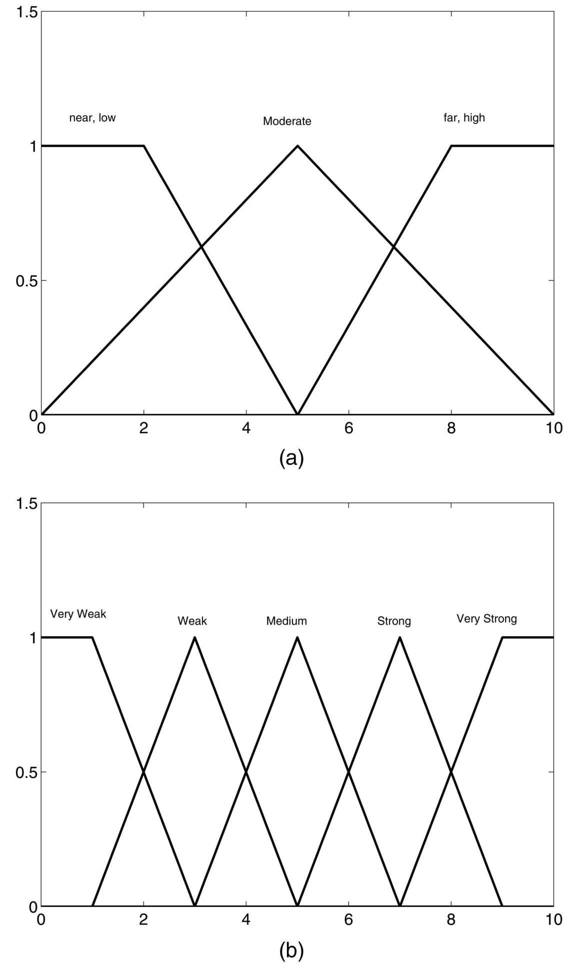


Fig. 3. MFs used to represent linguistic labels. (a) MFs for antecedents. (b) MFs for consequent.

2) The second antecedent is the frequency of appearance of such type of target based on some a priori knowledge such as archival radar data. Generally threat targets are new compared to archival radar data.

3) The third antecedent is the importance of geolocation of this target based on the geographical information systems (GISs). Examples of important geolocations include large metroplexes, landmarks, military bases, airports, etc. Threats happen quite often in such areas.

The above three antecedents are all knowledge based and it can be collected from the INT sensors. A typical rule using the above three antecedents can be:

> IF the number of switches from nonmaneuvering set to the maneuvering set is high, and the frequency of appearance of such target is low, and the importance of geolocation of such type of target is high, THEN the possibility that an I&W needs to be issued is very strong.

The linguistic variables used to represent each antecedent are divided into three levels: low, moderate, and high. The consequent—the possibility that an I&W needs to be issued—is divided into 5 levels, very strong, strong, medium, weak, very weak. So we need to set up $3^3 = 27$ (because every antecedent has 3 fuzzy subsets, and there are 3 antecedents) rules for this FLS. Table I summarizes the fuzzy rules we use in this paper. We use trapezoidal membership functions (MFs) to represent low, and high, and triangle MFs to represent moderate. We show these MFs in Fig. 3.

For input (x_1, x_2, x_3), the output is computed using

$$y(x_1,x_2,x_3) = \frac{\sum_{l=1}^{27} \mu_{F_l^1}(x_1)\mu_{F_l^2}(x_2)\mu_{F_l^3}(x_3)c_{\text{avg}}^l}{\sum_{l=1}^{27} \mu_{F_l^1}(x_1)\mu_{F_l^2}(x_2)\mu_{F_l^3}(x_3)} \qquad (3)$$

where $\mu_{F_l^i}(x_i)$ $(i = 1,2,3)$ represents the antecedent i membership degree (in the lth rule) when the input is x_i and the membership functions are plotted in Fig. 3. By repeating these calculations for $\forall x_i \in [0,10]$, we obtain a hypersurface $y(x_1,x_2,x_3)$. This equation represents the nonlinear mapping between three inputs and one output of the FLS. Since it's a 4-D surface (x_1,x_2,x_3,y), it's impossible to be plotted visually.

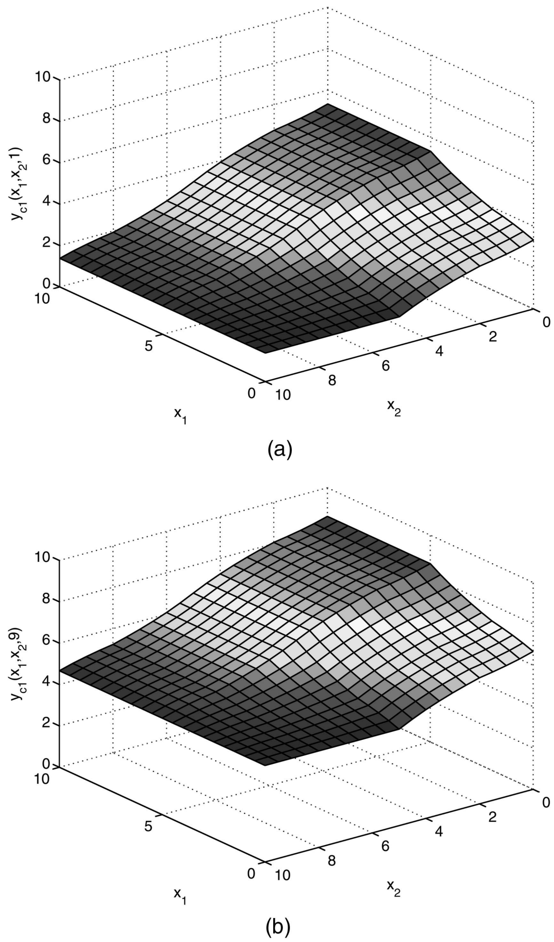


Fig. 4. Threat assessment surface for fixed importance of geolocation of this target (x_3). (a) When $x_3 = 1$. (b) When $x_3 = 9$.

If we have $x_3 = 1$, and two other antecedents x_1 and x_2 are variables, the output is computed using

$$y(x_1, x_2, 1) = \frac{\sum_{l=1}^{27} \mu_{\mathrm{F}_l^1}(x_1)\mu_{\mathrm{F}_l^2}(x_2)\mu_{\mathrm{F}_l^3}(1) c_{\cos}^l}{\sum_{l=1}^{27} \mu_{\mathrm{F}_l^1}(x_1)\mu_{\mathrm{F}_l^2}(x_2)\mu_{\mathrm{F}_l^3}(1)}. \quad (4)$$

This equation represents the nonlinear mapping between three inputs (one of which is fixed) and one output of the FLS. By repeating these calculations for $\forall x_1 \in [0, 10]$ and $\forall x_2 \in [0, 10]$, we obtain a hypersurface $y(x_1, x_2, 1)$, as plotted in Fig. 4(a). In contrast, if we have $x_3 = 9$, and two other antecedents x_1 and x_2 are variables, we obtain another surface $y(x_1, x_2, 9)$, as plotted in Fig. 4(b). Observe that from Fig. 4, the importance of geolocation of a target (x_3) makes a big difference in situation awareness, and the number of switches from nonmaneuvering set to the maneuvering set or vice versa (x_1) and the frequency of appearance of such target (x_2) also play a very important role even when the importance of geolocation (x_3) is the same.

IV. FINE TARGET RECOGNITION AND THREAT ASSESSMENT

A. Target RCS Value Estimation using RSNs

1) *RCS and RCS Voltage for Fluctuating Target*: Most radar analysis and measurement programs emphasize RCS measurements, which are proportional to received power. RCS is the fictional area over which the transmitter power density must be intercepted to collect a total power that would account for the received power density. Typical values of RCS for targets of interest range from 0.01 m^2 to hundreds of square meters [26]. Fluctuating target modeling is more realistic in which the target RCS is drawn from either the Rayleigh/exponential or chi-square of degree four probability density function (pdf). The Rayleigh/exponential model describes the behavior of a complex target consisting of many scatters, none of which is dominant. The fourth-degree chi-square model targets have many scatters of similar strength with one dominant scatter. Based on different combinations of pdf and decorrelation characteristics (scan-to-scan or pulse-to-pulse decorrelation), four Swerling models are used [24]. In this paper, we focus on "Swerling II" model which is an exponential distribution with pulse-to-pulse decorrelation. The pulse-to-pulse decorrelation implies that each individual pulse results in an independent value for RCS. Sometimes the RCS voltage value (square root of RCS) is of interest, particularly for use in simulations to model the composite echo from a multiple-scatter target. The RCS voltage value is the square root of RCS, so the pdf of RCS voltage follows a Rayleigh distribution [24]. In this paper, we apply radar sensor networks to estimate the RCS value.

2) *Introduction to Radar Sensor Networks*: In [11], we performed the following theoretical studies on CF pulse waveform design and diversity in RSNs: 1) the conditions for waveform coexistence, 2) interferences among waveforms in RSN, and 3) waveform diversity combining in RSN.

For RSNs, the waveforms from different radars interfere with each other. We choose the waveform for radar i as

$$x_i(t) = \sqrt{\frac{1}{T}} \exp[j2\pi(\beta + \delta_i)t], \qquad -T/2 \le t \le T/2 \quad (5)$$

where β is the RF carrier frequency in radians per second, and δ_i is a frequency shift for radar i. To minimize the interference from one waveform to the other, optimal values for δ_i should be determined to have the waveforms orthogonal to each other, i.e., let the cross-correlation between $x_i(t)$ and $x_n(t)$ be 0. We showed that choosing $\delta_i = i/T$ in (5) can have orthogonal waveforms, i.e., the waveforms can

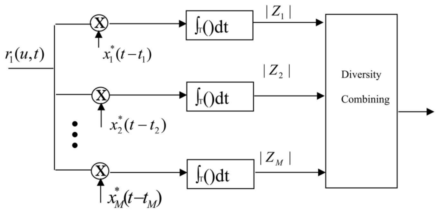


Fig. 5. Waveform diversity combining by clusterhead in RSN.

coexist if the carrier spacing is $1/T$ between two radar waveforms.

In RSN, the radar sensors are networked together in an ad hoc fashion. They do not rely on a preexisting fixed infrastructure, such as a wireline backbone network or a base station. They are self-organizing entities that are deployed on demand in support of various event surveillance, battlefield, disaster relief, search and rescue, etc. Scalability concern suggests a hierarchical organization of RSNs with the lowest level in the hierarchy being a cluster. As argued in [15], [8], [7], [22], in addition to helping with scalability and robustness, aggregating sensor nodes into clusters has additional benefits:

1) conserving radio resources such as bandwidth,
2) promoting spatial code reuse and frequency reuse,
3) simplifying the topology, e.g., when a mobile radar changes its location, it is sufficient for the nodes in attended clusters to update their topology information,
4) reducing the generation and propagation of routing information,
5) concealing the details of global network topology from individual nodes.

In RSN, each radar can provide its waveform parameters such as δ_i to its clusterhead radar, and the clusterhead radar can combine the waveforms from its cluster members.

In RSN with M radars, the received signal for clusterhead (assume it's radar 1) is

$$r_1(u,t) = \sum_{i=1}^{M} \alpha(u) x_i(t-t_i)\exp(j2\pi F_{D_i} t) + n(u,t) \tag{6}$$

where $x_i(t)$ is the transmitted CF waveform, $\alpha(u)$ stands for voltage of RCS, F_{D_i} is the Doppler shift of target relative to waveform i, t_i is the delay of waveform i, and $n(u,t)$ is the additive white Gaussian noise (AWGN). In [11], we proposed a RAKE structure for waveform diversity combining, as illustrated by Fig. 5.

According to this structure, the received $r_1(u,t)$ is processed by a bank of matched filters, then the output of branch 1 (after integration and before taking the envelope) is [11]

$$\begin{aligned} &Z_1(u;t_1,\ldots,t_M,F_{D_1},\ldots,F_{D_M}) \\ &\quad= \int_{-T/2}^{T/2} r_1(u,t)x_1^*(t-t_1)dt \qquad (7)\\ &\quad= \int_{-T/2}^{T/2}\left[\sum_{i=1}^{M}\alpha(u)x_i(t-t_i)\exp(j2\pi F_{D_i}t) + n(u,t)\right]x_1^*(t-t_1)dt \qquad (8)\end{aligned}$$

where $\int_{-T/2}^{T/2} n(u,t)x_1^*(t-t_1)dt$ can easily be proved to be AWGN. Let

$$n(u,t_1) \triangleq \int_{-T/2}^{T/2} n(u,t)x_1^*(t-t_1)dt. \tag{9}$$

Assuming $t_1 = t_2 = \cdots = t_M = \tau$, then according to interference analysis in [11],

$$\begin{aligned} Z_1(u;\tau,F_{D_1},\ldots,F_{D_M}) \approx& \sum_{i=2}^{M}\alpha(u)\mathrm{sinc}[\pi(i-1+F_{D_i}T)] \\ &+ \frac{\alpha(u)\sin[\pi F_{D_1}(T-|\tau|)]}{T\pi F_{D_1}} + n(u,\tau). \end{aligned} \tag{10}$$

Similarly, we can get the output for any branch m $(m = 1,2,\ldots,M)$,

$$\begin{aligned} Z_m(u;\tau,F_{D_1},\ldots,F_{D_M}) \approx& \sum_{i=1,i\neq m}^{M}\alpha(u)\mathrm{sinc}[\pi(i-m+F_{D_i}T)] \\ &+ \frac{\alpha(u)\sin[\pi F_{D_m}(T-|\tau|)]}{T\pi F_{D_m}} + n(u,\tau). \end{aligned} \tag{11}$$

Therefore $Z_m(u;\tau,F_{D_1},\ldots,F_{D_M})$ consists of three parts, signal (reflected signal from radar m waveform): $\alpha(u)E\sin[\pi F_{D_m}(T-|\tau|)]/T\pi F_{D_m}$, interferences from other waveforms: $\sum_{i=1,i\neq m}^{M}\alpha(u)E\mathrm{sinc}[\pi(i-m+F_{D_i}T)]$, and noise: $n(u,\tau)$.

We can have three special cases for $Z_m(u;\tau,F_{D_1},\ldots,F_{D_M})$.

1) When $F_{D_1} = \cdots = F_{D_M} = 0$,

$$Z_m(u;\tau,0,0,\ldots,0) \approx \frac{\alpha(u)(T-|\tau|)}{T} + n(u,\tau) \tag{12}$$

which means if there is no Doppler mismatch, there will be no interference from other waveforms.

2) If $\tau = 0$, then (11) becomes

$$\begin{aligned} Z_m(u;0,F_{D_1},\ldots,F_{D_M}) \approx& \sum_{i=1,i\neq m}^{M}\alpha(u)\mathrm{sinc}[\pi(i-m+F_{D_i}T)] \\ &+ \alpha(u)\mathrm{sinc}[\pi F_{D_m}T] + n(u). \end{aligned} \tag{13}$$

3) If $\tau = 0$, and $F_{D_1} = \cdots = F_{D_M} = 0$, then (11) becomes

$$Z_m(u;0,0,0,\ldots,0) \approx \alpha(u) + n(u). \tag{14}$$

Doppler mismatch happens quite often in target search where target velocity is not known yet. However, in target recognition, generally high-resolution measurements of targets in range ($\tau = 0$) and Doppler are available, so (14) will be used for RCS value estimation.

How to combine all the Z_ms ($m = 1,2,\ldots,M$) is very similar to the diversity combining in communations to combat channel fading, and the combination schemes may be different for different applications. In this paper, we are interested in applying RSN waveform diversity to estimate the RCS parameter γ^2, and we propose an ML algorithm for RCS parameter estimation.

3) *Maximum Likelihood Algorithm for RCS Parameter Estimation*: For the Swerling II model, the RCS voltage $|\alpha(u)|$ follows a Rayleigh distribution and the I and Q subchannels of $\alpha(u)$ follow zero-mean Gaussian distributions with a variance γ^2 (the RCS average power value). Assume

$$\alpha(u) = \alpha_I(u) + j\alpha_Q(u) \tag{15}$$

and $n(u) = n_I(u) + jn_Q(u)$ follows a zero-mean complex Gaussian distribution with a variance σ^2 for the I and Q subchannels.

According to (14),

$$|Z_m(u;0,0,0,\ldots,0)| \approx |\alpha(u) + n(u)|. \tag{16}$$

Since $\alpha(u)$ and $n(u)$ are zero-mean complex Gaussian random variables, $\alpha(u) + n(u)$ is a zero-mean Gaussian random variable with a variance $\gamma^2 + \sigma^2$ for the I and Q subchannels, which means $y_m \triangleq |Z_m(u;0,0,\ldots,0)|$ follows a Rayleigh distribution with parameter $\sqrt{\gamma^2 + \sigma^2}$,

$$f(y_m) = \frac{y_m}{\gamma^2 + \sigma^2} \exp\left[-\frac{y_m^2}{2(\gamma^2 + \sigma^2)}\right]. \tag{17}$$

The mean value of y_m is $\sqrt{\pi(\gamma^2 + \sigma^2)/2}$, and its variance is $(4-\pi)(\gamma^2 + \sigma^2)/2$. The variance of signal is $(4-\pi)\gamma^2/2$ and the variance of noise is $(4-\pi)\sigma^2/2$.

Let $\mathbf{y} \triangleq [y_1, y_2, \ldots, y_M]$, then the pdf of $\mathbf{y}$ is

$$f(\mathbf{y}) = \prod_{m=1}^{M} f(y_m) \tag{18}$$

$$= \prod_{m=1}^{M} \frac{y_m}{\gamma^2 + \sigma^2} \exp\left[-\frac{y_m^2}{2(\gamma^2 + \sigma^2)}\right] \tag{19}$$

let

$$\theta \triangleq \gamma^2 \tag{20}$$

then (19) can be expressed as

$$f(\mathbf{y}) = \prod_{m=1}^{M} \frac{y_m}{\theta + \sigma^2} \exp\left[-\frac{y_m^2}{2(\theta + \sigma^2)}\right]. \tag{21}$$

Therefore the ML algorithm to estimate the RCS average value (θ) can be represented as

$$\begin{aligned} \hat{\theta}_{\mathrm{ML}}(\mathbf{y}) &= \arg\sup_{\theta \in R^+} f(\mathbf{y}) \\ &= \arg\sup_{\theta \in R^+} \prod_{m=1}^{M} \frac{y_m}{\theta + \sigma^2} \exp\left[-\frac{y_m^2}{2(\theta + \sigma^2)}\right]. \end{aligned} \tag{22}$$

Maximizing $f(\mathbf{y})$ is equivalent to maximizing $\log f(\mathbf{y})$ (natural logarithm),

$$\log f(\mathbf{y}) = \sum_{m=1}^{M} \left[\log\left(\frac{y_m}{\theta + \sigma^2}\right) - \frac{y_m^2}{2(\theta + \sigma^2)}\right]. \tag{23}$$

Since it is a continuous function for $y_m > 0$ and $\theta > 0$, a necessary condition for the ML estimation is

$$\frac{\partial}{\partial\theta} \log f(\mathbf{y})|_{\theta = \hat{\theta}_{\mathrm{ML}}(\mathbf{y})} = \frac{\sum_{m=1}^{M} y_m^2 - 2M(\theta + \sigma^2)}{2(\theta + \sigma^2)^2} = 0 \tag{24}$$

which has the unique solution

$$\hat{\theta}_{\mathrm{ML}}(\mathbf{y}) = \frac{\sum_{m=1}^{M} y_m^2}{2M} - \sigma^2. \tag{25}$$

Considering $\theta \geq 0$,

$$\hat{\theta}_{\mathrm{ML}}(\mathbf{y}) = \max\left[\frac{\sum_{m=1}^{M} y_m^2}{2M} - \sigma^2, 0\right]. \tag{26}$$

Since

$$\frac{\partial^2}{\partial\theta^2} \log f(\mathbf{y})|_{\theta = \hat{\theta}_{\mathrm{ML}}(\mathbf{y})} = -\frac{4M^3}{(\sum_{m=1}^{M} y_m^2)^2} < 0 \tag{27}$$

this solution gives the unique maximum of $\log f(\mathbf{y})$. The expectation of $\hat{\theta}_{\mathrm{ML}}(\mathbf{y})$ is

$$E_\theta[\hat{\theta}_{\mathrm{ML}}(\mathbf{y})] = \int_0^\infty \frac{\sum_{m=1}^{M} y_m^2}{2M} f(y_m)dy_m - \sigma^2 \tag{28}$$

$$\begin{aligned} &= \int_0^\infty \frac{\sum_{m=1}^{M} y_m^2}{2M} \frac{y_m}{\theta + \sigma^2} \exp\left[-\frac{y_m^2}{2(\theta + \sigma^2)}\right] dy_m - \sigma^2 \\ &= \theta. \end{aligned} \tag{29}$$

Therefore it's an unbiased estimator.

Fisher's information for this case can be computed via

$$\begin{aligned} I_\theta &= -E_\theta\left[\frac{\partial^2}{\partial\theta^2} \log f(\mathbf{y})\right] \\ &= -E_\theta\left[\frac{M(\theta + \sigma^2) - \sum_{m=1}^{M} y_m^2}{(\theta + \sigma^2)^3}\right]. \end{aligned} \tag{30}$$

The mean value of y_m is $\sqrt{\pi(\theta + \sigma^2)/2}$, and its variance is $(4-\pi)(\theta + \sigma^2)/2$. So the Cramer-Rao lower bound (CRLB) is

$$\mathrm{Var}_\theta[\hat{\theta}(\mathbf{y})] \geq \frac{1}{I_\theta} = \frac{(\theta + \sigma^2)^2}{M}. \tag{31}$$

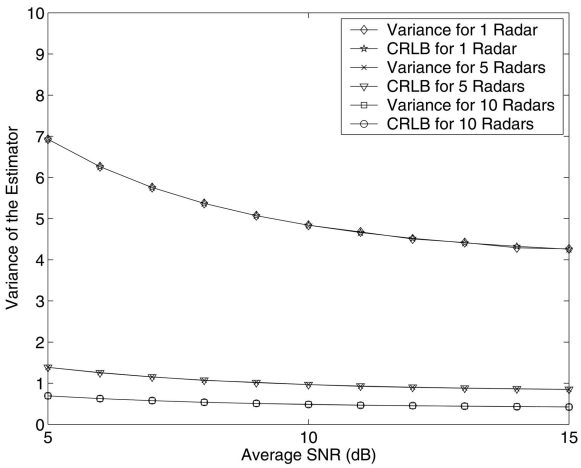


Fig. 6. Variance of RCS ML estimator with different number of radars in RSN.

Since $(\partial/\partial\theta)\log f(\mathbf{y})$ in (24) is of the form $k(\theta)[\hat{\theta}_{\mathrm{ML}}(y) - E_\theta[\hat{\theta}(\mathbf{y})]$ for

$$k(\theta) = \frac{M}{(\theta+\sigma^2)^2} \tag{32}$$

we conclude that $\hat{\theta}_{\mathrm{ML}}(\mathbf{y})$ can achieve the CRLB theoretically [17]. From (31), it's clear that CRLB is inversely proportional to the number of radars M in RSN, which means RSN with larger M will have much lower CRLB. This conclusion is drawn based on the assumption that the radar pulses are independent (in time and space) and follow a Rayleigh distribution, which is the Swerling II model [24].

4) *Simulations*: For fluctuating target with an RCS parameter $\theta = 2$ (Rayleigh distribution), we ran Monte Carlo simulations for 10^6 realizations at each SNR value, and we applied the ML estimation algorithm to estimate the parameter $\hat{\theta}$ for each realization. In Fig. 6, we plotted the variance of the RCS ML estimator with different number of radars in RSN. Observe the following.

1) The actual variance of $\hat{\theta}$ matches exactly with the CRLB for different numbers of radars in RSN, which validates our theoretical results: our ML estimator on the RCS parameter is an unbiased estimator and the variance of the parameter estimation matches CRLB.

2) The actual variance of $\hat{\theta}$ reduces as M increases, and numerically it is reversely proportional to M as we have shown in Section IVA.

B. Threat Assessment

Based on the estimated RCS value (for fine target recognition) and situation awareness-related I&W, threat can be assessed. For example, if an I&W was issued in Step 1 (situation awareness) on an unidentified flying object, we proceed with Step 2. In Step 2, based on Step 2 RCS value estimation, the target, for example, could be recognized as a bird, a missile, or other because a bird has an average RCS value of 0.01 m^2 and a conventional unmanned winged missle has an average RCS value of 0.5 m^2 [24]. A bird means the I&W is a false alarm, and a missile means the I&W is a threat and immediate actions need to be taken. The threat assessment results can be feedback to Step 1 to tune the design parameters of the FLS using training methods (for example, the steepest descent algorithm [13]).

V. CONCLUSIONS AND FUTURE WORKS

We have proposed a KUPS for threat assessment, of which "sensor" is a broad characterization concept, and it can be organic sensors, HUMINT sensors, SIGINT sensors, etc. Our KUPS for threat assessment consists of two major steps: situation awareness based on FLSs, fine target recognition (using RSNs), and threat assessment. Our FLSs can combine the linguistic knowledge from different intelligent sensors which contains lots of uncertainties. We propose an ML estimation algorithm for target RCS parameter estimation. Theoretically we show that our ML estimator is unbiased and the variance of parameter estimation matches the CRLB. Simulations further validate these theoretical results.

The proposed techniques will increase the sensitivity and performance of existing and future NCW, enhancing ship self-defense modes against stealthy, sea skimming, and antiship cruise missiles. In future works, we will also infer intent of objects/entities, or groups of objects, in the regions of interest. We will also study methods for constructing and learning a wide variety of models of threat behavior and methods for reasoning with uncertain and incomplete information for assessing threats from object activities.

ACKNOWLEDGMENT

Dr. Liang would like to thank ONR Program Officer Dr. Rabinder N. Madan for his direction and insightful discussion on RSNs.

REFERENCES

[1] Command and Control and Combat Systems (C2 and CS). ONR BAA 06-016.

[2] Cai, Y. et al. A situation and threat assessment model based on group analysis. In *Proceedings of the 2005 International Conference on Machine Learning and Cybernetics*, Aug. 2005, 356–361.

[3] Choi, J. W., Joo, J. W. and Cho, D. L. Situation/threat assessment fusion system (STAFS). In *Proceedings of the Fifth International Conference on Information Fusion*, July 2002, 1374–1380.

[4] Changwen, Q., and You, H.
A method of threat assessment using multiple attribute decision making.
In *6th International Conference on Signal Processing*, Aug. 2002, 1091–1095.

[5] Dall, I. W.
Threat assessment without situation assessment.
In *Proceedings of Information, Decision and Control*, Feb. 1999, 365–370.

[6] Gonsalves, P. et al.
Intelligent threat assessment processor (ITAP) using genetic algorithms and fuzzy logic.
In *Proceedings of the Third International Conference on Information Fusion*, 2000.

[7] Hou, T.-C., and Tsai, T-J.
An access-based clustering protocol for multihop wireless ad hoc networks.
IEEE Journal of Selected Areas in Communications, **19**, 7 (July 2001), 1201–1210.

[8] Iwata, A., Chiang, C. C., Pei, G., Gerla, M., and Chen, T. W.
Scalable routing strategies for ad hoc networks.
IEEE Journal of Selected Areas in Communications, **17** (1999), 1369–1379.

[9] Jan, T.
Neural network based threat assessment for automated visual surveillance.
In *IEEE International Joint Conference on Neural Networks*, vol. 2, July 2004, 1309–1312.

[10] Leung, S. W., Minett, J. W., Siu, Y. M., and Lee, M. K.
A fuzzy approach to signal integration.
IEEE Transactions on Aerospace and Electronic Systems, **38**, 1 (Jan. 2002), 346–351.

[11] Liang, Q.
Waveform design and diversity in radar sensor networks: Theoretical analysis and application to automatic target recognition.
In *IEEE International Workshop on Wireless Ad Hoc and Sensor Networks*, June 2006, New York.

[12] Liang, Q.
Radar sensor networks: Algorithms for waveform design and diversity with application to atr with delay-Doppler uncertainty.
EURASIP Journal on Wireless Communications and Networking, (2007), 1–9.

[13] Liang, Q., and Mendel, J. M.
Interval type-2 fuzzy logic systems: Theory and design.
IEEE Transactions on Fuzzy Systems, **8**, 5 (Oct. 2000), 535–550.

[14] Lin, Y., Chen, B., and Varshney, P. K.
Decision fusion rules in multi-hop wireless sensor networks.
IEEE Transactions on Aerospace and Electronic Systems, **41**, 2 (2005), 476–489.

[15] Lin, C. R., and Gerla, M.
Adaptive clustering in mobile wireless networks.
IEEE Journal of Selected Areas in Communications, **16** (1997), 1265–1275.

[16] Mendel, J. M.
Fuzzy logic systems for engineering : A tutorial.
Proceedings of the IEEE, **83**, 3 (Mar. 1995), 345–377.

[17] Mendel, J. M.
Lessons in Estimation Theory for Signal Processing, Communications, and Control.
Upper Saddle River, NJ: Prentice-Hall, 1995.

[18] Mendel, J. M.
Uncertain Rule-Based Fuzzy Logic Systems.
Upper Saddle River, NJ: Prentice-Hall, 2001.

[19] Manley, J. E., Mineart, G. M., and Sheridan, A. E.
Underwater marine domain awareness for first responders: A low cost approach.
MTS/IEEE TECHNO-OCEAN '04 vol. 3, 2004, 1695–1700.

[20] Nguyen, X. T.
Threat assessment in tactical airborne environments.
In *Proceedings of the Fifth International Conference on Information Fusion*, July 2002.

[21] Okello, N., and Thorns, G.
Threat assessment using Bayesian networks.
In *Proceedings of the Sixth International Conference of Information Fusion*, vol. 2, 2003, 1102–1109.

[22] Perkins, C. E.
Cluster-based networks.
In C. E. Perkins (Ed.), *Ad Hoc Networking*, Reading, MA: Addison-Wesley, 2001, 75–138.

[23] Roman, J., Rangaswamy, M., Davis, D., Zhang, Q., Himed, B., and Michels, J.
Parametric adaptive matched filter for airborne radar applications.
IEEE Transactions on Aerospace and Electronic Systems, **36**, 2 (2000), 677–692.

[24] Richards, M. A.
Fundamentals of Radar Signal Processing.
New York: McGraw-Hill, 2005.

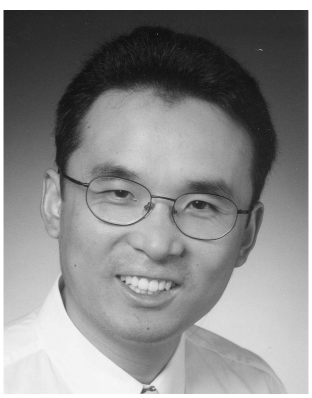
[25] Singh, R. P., Bailey, W. H.
Fuzzy logic applications to multisensor-multitarget correlation.
IEEE Transactions on Aerospace and Electronic Systems, **33**, 3 (July 1997), 752–769.

[26] Skolnik, M. I.
Introduction to Radar Systems (3rd ed.).
New York, McGraw-Hill, 2001.

[27] Swerling, P.
Probability of detection for fluctuating targets.
IRE Transactions on Information Theory, **6** (Apr. 1960), 269–308.

[28] Petterson, G. et al.
Multi-source integration and temporal situation assessment in air combat.
1999 Information, Decision and Control, (Feb. 1999), 371–375.

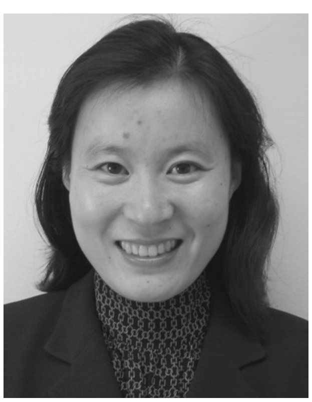
[29] Steinberg, A. N.
An approach to threat assessment.
In *2005 8th International Conference on Information Fusion*, vol. 2, July 2005.



Qilian Liang (M'01—SM'05) received the B.S. degree from Wuhan University in 1993, M.S. degree from Beijing University of Posts and Telecommunications in 1996, and Ph.D. degree from University of Southern California (USC), Los Angeles, in May 2000, all in electrical engineering.

He joined the faculty of the University of Texas at Arlington in August 2002 and is currently an associate professor. Prior to that he was a member of the technical staff in Hughes Network Systems Inc. at San Diego, CA. His research interests include sensor networks, wireless communications, wireless networks, communication system and communication theory, signal processing for communications, fuzzy logic systems and applications, collaborative and distributed signal processing.

Dr. Liang has published more than 120 journal and conference papers, 6 book chapters, and has 6 U.S. patents pending. He received the 2002 IEEE Transactions on Fuzzy Systems Outstanding Paper Award, the 2003 U.S. Office of Naval Research (ONR) Young Investigator Award, and the 2005 UTA College of Engineering Outstanding Young Faculty Award.



Xiuzhen (Susan) Cheng (M'02) received her M.S. and Ph.D. degrees in computer science from the University of Minnesota–Twin Cities, in 2000 and 2002, respectively.

She is an associate professor in the Department of Computer Science at the George Washington University. Her current research interests include wireless and mobile computing, sensor networking, wireless and mobile security, and approximation algorithm design and analysis.

Dr. Cheng has served on the editorial boards of several technical journals and in the technical program committees of various professional conferences/workshops. She was the program cochair of the first International Conference on Wireless Algorithms, Systems, and Applications (WASA06). She worked as a program director in the National Science Foundation for six months in 2006. She received the NSF CAREER Award in 2004.