Threat-Based Sensor Management for Target Tracking

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A sensor management scheme that focuses on managing the uncertainty in the threat level of targets is proposed. The scheme selects the best sensing mode such that the uncertainty in the threat level of targets is minimized. The main advantage of the proposed scheme is that it opens the possibility for incorporation of the operational context when performing Bayes-optimal sensor management. Different aspects of threat can be meaningfully aggregated making this flexible approach a favorite choice for multifunctional systems. The proposed scheme is demonstrated in simulated scenarios, both simple and advanced, where the data association problem is taken into account. In the multitarget example, the proposed scheme outperforms the other schemes considered in this manuscript, both naive and adaptive. The proposed scheme can be used in target tracking applications, such as air traffic management or area surveillance.

Manuscript received January 20, 2014; revised May 26, 2014, February 20, 2015; released for publication June 30, 2015.

DOI. No. 10.1109/TAES.2015.140052.

Refereeing of this contribution was handled by S. Coraluppi.

F. Katsilieris was affiliated with Thales Nederland B.V. until the 31st of August 2013. During this period, he was funded by the EU's Seventh Framework Programme Grant 238710 within the MC IMPULSE project: https://mcimpulse.isy.liu.se. From the 1st of September 2013 until the 1st of April 2014, F. Katsilieris was affiliated with the Delft University of Technology and was funded by the Dutch Government for the Sensor Technology Applied in Reconfigurable systems for sustainable Security (STARS) project: www.starsproject.nl. The majority of the research was conducted under the MC Impulse project, the preparation of the manuscript was conducted under the STARS project.

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I. INTRODUCTION

In many practical problems it is desired to use a series of observations in order to infer the state of a system. A typical example is area defence where flying objects are tracked using radar measurements, with the possibility of using different sensing modes in order to improve the tracking performance. For instance, different waveforms or beam positions can be selected. The aforementioned problem of selecting the best sensing mode is commonly referred to using the terms sensor management or resource allocation.

For several years, rule-based approaches have been the workhorse of sensor management [1]. This was mainly dictated by the complexity of the sensor management problem, limitations in computing resources, and requirements for real-time operation. Over the last few decades computing resources have become increasingly available and the focus has shifted to approaches that are optimal in the Bayesian sense. Accordingly, this paper focuses only on approaches that are optimal in the Bayesian sense.

Within the Bayesian decision theory context, a loss (or utility) function is defined that is associated with performing a wrong decision. Since the quality of a decision depends on the unknown true state of the system and the corresponding measurement, the expected loss can be evaluated under the assumption that both the state of the system and the measurement have given probability distributions. This expected loss is the risk function of a decision rule and the goal is to choose the action that yields the minimum risk [2].

In the first Bayes optimal approach, the loss function is a function of the state(s) of the system that are of interest to the task that must be performed. Hence, the name task-based criteria. Typical examples of task-based loss/utility functions when tracking targets are: 1) the expected trace/determinant of the covariance matrix of the estimated system's states probability density function (pdf) [3], where one seeks to minimize the expected trace/determinant of the covariance matrix of the target state's estimate; 2) the deviation from an ideal covariance matrix [4], where one seeks to minimize the difference between the covariance matrix of the target state's estimate and a predefined covariance matrix; and 3) in the multitarget tracking context, the posterior expected number of targets (PENT) [5], where one tries to maximize the targets to be observed by a sensor.

A second approach, which has emerged in the last years, is to follow an information theoretic approach to sensor management, hence the name information-driven sensor management. This approach is characterized by a measure of the information theoretic notion of uncertainty, i.e., the Shannon entropy and its generalization the Rényi entropy. Another popular information theoretic utility function is the Kullback-Leibler divergence (KLD) [6–10]. It has also been shown that for sensor management purposes, using the conditional entropy or the KLD leads to the same sensor selection [11].

The two aforementioned approaches have certain practical shortcomings, as also discussed in [12]. They might not translate easily to the desired operational performance of the system or be too difficult to explain to a system operator. For example, it is not clear what is the practical explanation of the information theoretic criteria [11, 13, 14] (except for a very specific example [10]). Furthermore, in some scenarios several criteria must be taken into account simultaneously. This can lead to a multiobjective optimization problem that can be very challenging to solve, especially in real-time. A simple workaround is to follow a weighted-sum approach but it might not always make physical or operational sense to do so. Consider, for example, an application where the operator is not only interested in the accuracy of the target position and velocity but also in its interaction with other targets or its overall behavior. In such case, a weighted sum of the expected trace of the covariance matrix and of the distance between the target and an asset could be used but what would be its mathematical meaning and how would it relate to the operational goal of the system? A major disadvantage of the task-based and information-driven criteria is that they are not adaptive to the user needs. In other words, the user cannot tune them in order to address the needs of different operational contexts because these criteria have a strict mathematical definition. This is exactly the practical disadvantage that our proposed approach addresses.

To resolve the problems mentioned above, a third approach has been presented in [15, 16]. In this approach, the notion of operational risk is used as a utility function for performing sensor management, hence the name risk-based sensor management.[1] Accordingly, the risk (or in some cases threat) level of each target is used for allocating the sensor resources and taking actions. Somewhere in-between the task-based and the risk-based approaches lies an extension of PENT, namely the predicted expected number of targets of interest (PENTI) [17]. The risk-based approach has the advantage that it addresses exactly what the user considers relevant in a given operational context. Revisiting the example from the target tracking context, the operator might not be directly interested in knowing the exact position of an aircraft but instead in having a clear idea of whether this aircraft is a threat to a specific asset and then take actions accordingly. This process is also called threat assessment and therefore, for the purposes of clarity from now on we will call this approach the threat-based approach to sensor management.

It is also worthwhile to point out that, considering the JDL model [18], the threat-based approach to sensor management constitutes a shift from level 1 based sensor management to level 2/3 based sensor management. This shift brings the sensor management objective closer to what the user is interested in [19].

In this paper, we develop further the idea initially suggested in [20] and propose performing sensor management such that the uncertainty in the target threat level is managed. In other words, we assume that the threat level is seen as a system state that cannot be affected (at least by only observing it—much like the position and the velocity of the target). Therefore, it is desirable to minimize the uncertainty in the threat level such that the operator can take decisions with lower (Bayes or operational) risk about whether and how to act. The novelty of our proposed method is the shift from allocating sensor resources according to the target threat level, to managing the uncertainty in the threat level. Examples of mathematical threat definitions are given for different operational contexts and it is shown how different aspects of threat can be aggregated in a consistent and meaningful manner, therefore circumventing the challenge of solving a multiobjective optimization problem or of formulating a nonmeaningful weighted sum objective.

While in [20] a very simplistic model of threat (the probability of detection is always one and false alarms are absent) in a defense context is considered, in this paper the threat modeling is generalized towards multiple practical applications by including detection uncertainty, false alarms, and an unknown number of true targets. Additionally, examples both from the defence (antenna beam positioning control in a multifunction radar used for asset defence) and from the civilian domain (air traffic control) are considered.

In Section II we give an overview of the system setup and the problem formulation. In Section III we present our proposed method, the threat-based approach to sensor management. Simulated examples are presented in Section IV and the paper is concluded with Section V.

II. SYSTEM SETUP AND PROBLEM FORMULATION

The threat-based sensor management approach is presented in the target tracking context. In order to focus on the sensor management instead of the filtering problem, the following assumptions are made.

For time step k of the filtering recursion, the time index $k-1$ denotes the prior, $k|k-1$ denotes the predicted, and k denotes the posterior distribution of a random variable.

The targets are assumed to move in the 2-dimensional space. The motion of each target[2] in the Cartesian coordinates is modeled using a nearly constant velocity model [21]. These assumptions do not limit the applicability of the proposed approach; they can be readily relaxed and more complicated target motion models can be used.

[1] Unfortunately, this already coined name can be misleading due to the conflict between operational risk and Bayes risk. For this reason, a different term is used for the proposed approach in this paper.

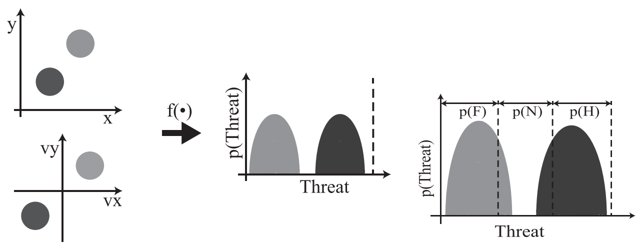
[2] For simplicity, the target index is omitted in this section.

A sensor provides range and bearing measurements of a target with states x_k according to

$$\mathbf{z}_k = \begin{bmatrix} \sqrt{x^2 + y^2} \\ \text{atan2}\,(y, x) \end{bmatrix} + \mathbf{v}_k \tag{1}$$

where $\mathbf{v}_k \sim \mathcal{N}(\mu_v, \Sigma_v)$, $\mu_v = [0\ 0]^{\mathrm{T}}$, $\Sigma_v = \text{diag}(\sigma_r^2, \sigma_b^2)$, atan2 is the four-quadrant inverse tangent function, and σ_r^2, σ_b^2 are the variances of the range and bearing measurements, respectively. This assumption can also be relaxed and more complicated measurement models can be used.

The problem considered in this paper is to decide which sensing action is best to perform at each time instance. The term "sensing action" refers to selecting the target to be observed and/or the accuracy of the sensor.



(a) The operator observes the behavior of the targets via their state estimates. The uncertainty in the states is translated in uncertainty in the threat level.

(b) The estimated threat level can be used for labeling the targets with a certain probability.

Fig. 1. Demonstration of threat assessment process for two targets, one incoming and one receding.

III. THREAT-BASED APPROACH TO SENSOR MANAGEMENT

As an alternative to the sensor management approaches discussed in the Introduction, we propose a threat-based approach. First, the idea leading to the threat-based approach, i.e., the threat assessment process, is explained along with its connection to sensor management. Secondly, it is shown how the threat-based approach to sensor management can be implemented. Accordingly, it is shown how different threat definitions can be formulated, aggregated in a meaningful and consistent manner and used for obtaining the threat pdf of a target. The threat pdf can be used for assigning threat labels to targets and for suggesting a course of action to the system operator. Finally, it is explained that the proposed sensor management scheme selects the sensing action that minimizes the uncertainty in the threat pdf as way of managing the uncertainty in the threat level of a target.

A. Threat Assessment and Its Connection to Sensor Management

It is very common in the military context to assign labels to the targets according to the threat that they pose to own assets or to mission success.[3] This set of labels can be defined as $\mathcal{L} = \{\ell_1, \ldots, \ell_{n_D}\}$, where ℓ_i can be "friendly," "neutral," or "hostile" for example. The operator estimates the correct label for each target by observing the overall target behavior and considering the operational context and the mission goals. This process is called threat assessment and is demonstrated in Fig. 1 (a) and (b). In the presented example, a threat label is assigned to every partition of the threat space according to the operational needs.

In practice, threat assessment is performed based not only on kinematic information but also on additional contextual information. Such contextual information can be, for instance, intelligence about expected threat types and their capability and intent; see for example the discussion and models in [15] and [24]. In this paper, we model threat only based on observable kinematic properties of targets. This simplification is motivated by the limitations in modeling all aspects of interest but nevertheless gives a proof of concept of performing sensor management based on the threat level of targets. In other words, the method proposed in this paper can be seen as a first step towards JDL level 2/3 sensor management.

In terms of mathematics, the threat θ that a target poses can be seen as a state to be estimated along with the standard state vector that includes the target's position and velocity. A threat function $f : \mathcal{S} \mapsto \mathcal{T}$ is defined as a map from the conventional elements of the single target state space (typically 2D/3D position and velocity) $\mathcal{S} = \mathbb{R}^n$ to the elements of the single target threat space $\mathcal{T} = [0, 1]$ according to the operational context. In multitarget scenarios, each individual target state space is mapped to its individual threat space.

The threat function is the mathematical translation of what the operator classifies as threat. Because the threat is a function of random variables, such as the position and velocity of the targets, the threat is also a random variable, whose pdf is found by utilizing the user-defined threat function(s). The threat pdf $p(\theta)$ is important because it can be used for assigning a threat label to a target and for suggesting a course of action to the system operator. In a military, asset-defence scenario, the operator might use the threat pdf in order to decide whether to engage a target or not. In a civilian scenario, the operator might use the threat pdf in order to instruct a target to change its trajectory such that a collision is avoided. Threat functions for these specific scenarios are presented in the following subsection.

We propose selecting the best sensing action such that the uncertainty in the threat assessment process is minimized instead of allocating the resources according to the threat level of each target or minimizing the uncertainty in the target states. The proposed approach can lead to the operator taking decisions with less uncertainty

[3] In order to avoid the confusion between threat and risk, we follow the terminology used in [22] where Romberg describes an approach where objects are sought that threaten valuable assets. Romberg denominates those objects as threat and defines the expected loss of value as due to a possible event caused by these threats as risk. Also see [23, ch. 4.7].

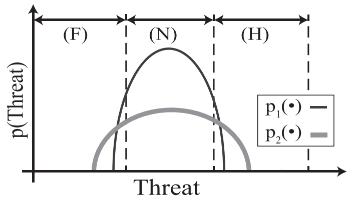


Fig. 2. An example of why lower uncertainty leads to better decisions. Both pdfs would result in labeling target as neutral but using p_1 would result in lower Bayes and operational risk.

and consequently with lower operational and Bayesian risk.

In order to demonstrate why we want to minimize the uncertainty in the threat distribution, we consider a simple example. Two possible threat distributions for a target are shown in Fig. 2 and one of the following three labels can be assigned to the target: {friendly (F), neutral (N), hostile (H)}. Each label could also imply that a certain course of action will be followed according to the operational context. The label probabilities are $p_i(F) = \int_0^{1/3} p_i(\theta)\mathrm{d}\theta$, $p_i(N) = \int_{1/3}^{2/3} p_i(\theta)\mathrm{d}\theta$, $p_i(H) = \int_{2/3}^{1} p_i(\theta)\mathrm{d}\theta$ where $i = 1, 2$. In both cases the label (N) would be chosen because $p_i(N) > \{p_i(F), p_i(H)\}$. Nevertheless, it is obvious that an operator would prefer to assign a threat label or take an action based on the first threat distribution due to its lower intrinsic uncertainty.

The importance of reducing the uncertainty in the threat, as per the proposed approach, is also evident when the object, orient, decide, and act (OODA) loop is considered in the military context. As discussed in the review paper [24, ch. 3,5,8] and the references therein, reduced uncertainty in threat leads to a better OODA loop, which in turn gives a significant advantage over the adversary.

B. Threat Definitions and How to Aggregate Them

The mathematical formulation of the threat definition must in principle take into account what the operator classifies as threat in a given context and by definition it must hold that threat $\theta \in [0,1]$.

In order to motivate our approach, three threat functions are given for two examples: one drawn from the defence domain and one from the civilian domain. In both examples, we use the notions of range to the closest point of approach (CPA) and time to the CPA. Time and range to CPA are two quantities that can be used for modeling several aspects of threat, as threat is described in the bibliography. In [23, 25] for example, it is stated that when a target approaches another target or an asset of interest then the operator must be notified because this is an event of interest, or in other words, one of the targets is a potential threat. In [26], time and range to CPA are parts of the situation geometry, situation projection, and timing analysis.

The example functions presented here are intentionally simple (i.e., only 2D motion of targets is considered) but sufficient for demonstrating the versatility of this threat-based approach. Ideally, the system operator can select the modeled aspects of threat, possibly from a library, to be taken into account according to the operational needs. Finally, it is demonstrated how different threat functions can be aggregated in a meaningful manner.

The time and range to CPA for two targets i and j with corresponding state vectors $\mathrm{x}^{(i)} = [x^{(i)}\ v_x^{(i)}\ y^{(i)}\ v_y^{(i)}]^{\mathbf{T}}$ and $\mathrm{x}^{(j)} = [x^{(j)}\ v_x^{(j)}\ y^{(j)}\ v_y^{(j)}]^{\mathbf{T}}$ are given by

$$t_{CPA} = -\frac{\mathrm{pos}_x \mathrm{vel}_x + \mathrm{pos}_y \mathrm{vel}_y}{\sqrt{\mathrm{vel}_x^2 + \mathrm{vel}_y^2}} \tag{2}$$

$$d_{CPA} = \sqrt{(\mathrm{pos}_x + t_{CPA}\mathrm{vel}_x)^2 + \left(\mathrm{pos}_y + t_{CPA}\mathrm{vel}_y\right)^2} \tag{3}$$

where

$$\mathrm{pos} = \left[\mathrm{pos}_x \quad \mathrm{pos}_y\right]^{\mathbf{T}} = \left[x^{(i)} \quad y^{(i)}\right]^{\mathbf{T}} - \left[x^{(j)} \quad y^{(j)}\right]^{\mathbf{T}} \tag{4}$$

$$\mathrm{vel} = \left[\mathrm{vel}_x \quad \mathrm{vel}_y\right]^{\mathbf{T}} = \left[v_x^{(i)} \quad v_y^{(i)}\right]^{\mathbf{T}} - \left[v_x^{(j)} \quad v_y^{(j)}\right]^{\mathbf{T}} \tag{5}$$

Let's consider an example from the military domain first, where an operator wants to protect asset j. The threat that is posed by a target i to asset j depends on how close and how fast the target i can come to asset j. In order to move from the time and range domain to the threat domain, a sigmoid function can be utilized for example[4]:

$$\theta_t\left(\mathrm{x}^{(i)}; \mathrm{x}^{(j)}\right) = \begin{cases} 1, & |t_{CPA}| \le t_1 \\ 1 - 2\left(\frac{|t_{CPA}| - t_1}{t_0 - t_1}\right)^2, & t_1 < |t_{CPA}| \le t_{0.5} \\ 2\left(\frac{|t_{CPA}| - t_0}{t_0 - t_1}\right)^2, & t_{0.5} < |t_{CPA}| \le t_0 \\ 0, & t_0 < |t_{CPA}| \end{cases} \tag{6}$$

$$\theta_d\left(\mathrm{x}^{(i)}; \mathrm{x}^{(j)}\right) = \begin{cases} 1, & d_{CPA} \le d_1 \\ 1 - 2\left(\frac{d_{CPA} - d_1}{d_0 - d_1}\right)^2, & d_1 < d_{CPA} \le d_{0.5} \\ 2\left(\frac{d_{CPA} - d_0}{d_0 - d_1}\right)^2, & d_{0.5} < d_{CPA} \le d_0 \\ 0, & d_0 < d_{CPA} \end{cases} \tag{7}$$

where $t_1 < t_{0.5} < t_0$ and $d_1 < d_{0.5} < d_0$ are the points where the threat is equal to 1, 0.5, and 0.

Let's consider now an example from the civilian domain, e.g. an air traffic control application. The operator monitors the behavior of the targets and is interested in whether any two targets will collide with each other. The time and range to CPA can be utilized again in this example since they model conveniently whether and when two targets might collide, also see the discussion in [27, 28] about measures of effectiveness when performing air traffic management. The time and range to CPA among all pairs of targets (i, j), where $i, j = 1, \ldots, N$ and $i \neq j$, are

[4] The specific choice of sigmoid functions is only for demonstration purposes. In [20], for example, linear functions are used.

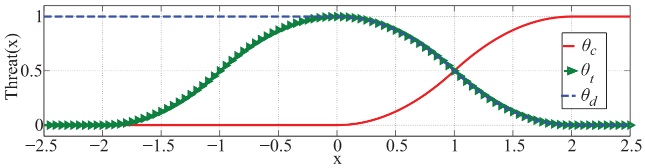


Fig. 3. Plots of defined threat functions, for gaining intuition about their shape.

considered rather than between each target and an asset. From the $N-1$ different threat values for a target i, the threat value j^* can be selected such that

$$\theta\left(\mathrm{x}^{(i)}\right) = \theta\left(\mathrm{x}^{(i)}; \mathrm{x}^{(j^*(i))}\right) \tag{8}$$

$$\begin{gathered} j^*(i) = \arg\max_{j(\ldots)} \hat{\theta}\left(\mathrm{x}^{(i)}; \mathrm{x}^{(j)}\right) \\ i, j = 1, \ldots, N \text{ and } i \neq j \end{gathered} \tag{9}$$

$$\hat{\theta}(\cdot) = \int \theta(\cdot) p\left(\theta(\cdot)\right) \mathrm{d}\theta(\cdot) \tag{10}$$

where N is the number of targets in the scenario.

When anomaly detection is of interest, deviation from trajectories or shipping lanes is an important quantity to be taken into account, as discussed in [29, 30]. If one would like to model the deviation of a target i from a given trajectory $\mathcal{C}$, then a similar mathematical approach can be followed. A sigmoid function can be used and the three distances $c_0 < c_{0.5} < c_1$ from the axis of a trajectory $\mathcal{C}$ must be defined where threat is equal to 0, 0.5, and 1, respectively. Then

$$\theta_c\left(\mathrm{x}^{(i)}; \mathcal{C}\right) = \begin{cases} 1, & c_1 < c_{min} \\ 1 - 2\left(\frac{c_{min} - c_1}{c_0 - c_1}\right)^2, & c_{0.5} < c_{min} \leq c_1 \\ 2\left(\frac{c_{min} - c_0}{c_0 - c_1}\right)^2, & c_0 < c_{min} \leq c_{0.5} \\ 0, & c_{min} \leq c_0 \end{cases} \tag{11}$$

where c_{min} is the minimum distance between the target and the given trajectory.

Fig. 3 demonstrates the defined threat functions for $[t_1\ t_{0.5}\ t_0] = [d_1\ d_{0.5}\ d_0] = [c_0\ c_{0.5}\ c_1] = [0, 1, 2]$.

Considering other aspects of threat that depend on measurable quantities, one could extend the state vector by including the corresponding quantities, e.g. descent rate, and then model mathematically their relation to threat much like it is presented above. A typical example would be to consider target classification when performing threat assessment, which would lead to mode-dependent threat definitions and would introduce corresponding modes to the threat pdf. When nonmeasurable aspects of threat, e.g. political climate, must be considered then the threat pdf could be skewed (or transformed in an appropriate way) in order to reflect this information.

After mapping to the same domain, i.e., threat, all quantities of interest (e.g. time and range to CPA, deviation from a given trajectory) it is meaningful to aggregate them using a weighted sum in order to evaluate the total threat level of a target i:

$$\theta\left(\mathrm{x}^{(i)}\right) = \sum_{j=1}^{M} m_j \theta_j\left(\mathrm{x}^{(i)}; \cdot\right) \tag{12}$$

where m_j is the weight assigned to $\theta_j(\mathrm{x}^{(i)}; \cdot)$ such that $\sum_{j=1}^{M} m_j = 1$. In this way we have simplified what would have been a multiobjective optimization problem to a simpler but still meaningful single objective problem that consists of the weighted sum of the different aspects of threat. In other words, instead of minimizing the uncertainty in the time/range to CPA and deviation from a given trajectory, the uncertainty in the total threat level is minimized. Furthermore, this is an improvement over the conventional weighted sum approaches because now commensurate quantities, i.e., aspects of threat, are summed.

C. Evaluating Uncertainty in Threat

As discussed in the previous subsections, threat can be seen as a derived state of each target and has a pdf that can depend, among others, on the target state's pdf and the operational context. Therefore, the uncertainty in the threat pdf can be evaluated using any of the popular approaches: for example, via its covariance or via its entropy (or equivalently for myopic sensor management purposes, the KLD). The best choice remains an open question, as explained in the Introduction.

IV. SIMULATED EXAMPLES

In the following subsections, we demonstrate that the proposed approach is easy to adapt to the operator requirements and that it gives meaningful sensor selections. This is done by defining different threat functions and discussing the corresponding sensor management results in a single- and in a multitarget scenario.

In all examples, the targets move in the 2-dimensional space and follow a nearly constant velocity model, as in [21].

A. Single Target Example: Aggregation of Threat Functions

In the first example, we consider a single target that is supposed to stay within a given corridor of 1 km total width along a predefined trajectory. The target can be observed by one radar with two different sensing modes: $\Sigma_1 = \mathrm{diag}(30^2\ \mathrm{m}^2, 1^2\ \mathrm{deg}^2)$ and $\Sigma_2 = \mathrm{diag}(10^2\ \mathrm{m}^2, 3^2\ \mathrm{deg}^2)$.

The first mode has much better angular accuracy whereas the second mode has much better range accuracy in order to strongly emphasize the differences between the two sensor management approaches. Depending on the relative position and velocity of a target to the radar, one of these two modes might be more favorable for tracking the target.

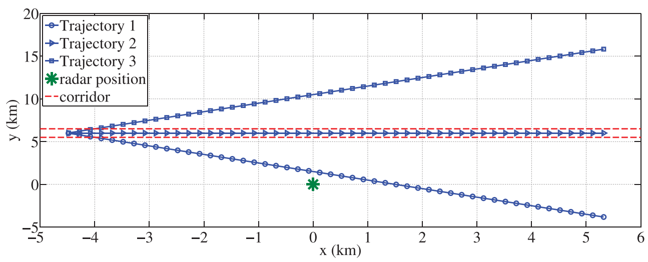
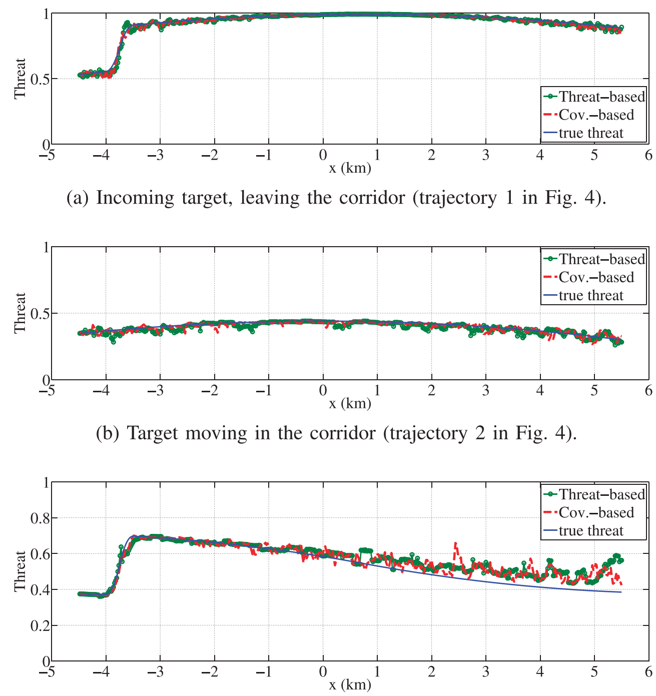


Fig. 4. Geometry of single-target example, along with three different target trajectories that are considered.



(a) Incoming target, leaving the corridor (trajectory 1 in Fig. 4).

(b) Target moving in the corridor (trajectory 2 in Fig. 4).

(c) Receding target, leaving the corridor (trajectory 3 in Fig. 4).

Fig. 5. Threat evolution of considered trajectories.

Fig. 4 demonstrates the geometry of the example, for three different target trajectories. In all cases the target starts at [–4.5, 6] km. Trajectory 1: Incoming target, leaving the corridor. The target has constant velocity of [20, –20] m/s. Trajectory 2: Target moving in the corridor. The target has constant velocity of [20, 0] m/s. Trajectory 3: Receding target, leaving the corridor. The target has constant velocity of [20, 20] m/s.

The target is tracked using an extended Kalman filter with a nearly constant velocity motion model where $T = 1$ s and $\sigma_x^2 = \sigma_y^2 = 5$ m/s. The filter is initialized with the correct target position/velocity and with covariance matrix $P = \mathrm{diag}(20^2\ \mathrm{m}^2,\ 2^2\ (\mathrm{m/s})^2\ 20^2\ \mathrm{m}^2,\ 2^2\ (\mathrm{m/s})^2)$. The duration of each scenario is 500 s.

The operator wants to take into account the following three aspects of threat: time to CPA, range to CPA (both with respect to the radar location), and the target distance from the center of the corridor around the predefined trajectory. The mathematical form of these threat definitions and their aggregation are the same as in Subsection III-B, with equal weights $m_1 = m_2 = m_3 = 1/3$ and

$$[t_1 \quad t_{0.5} \quad t_0] = [0 \quad 5 \quad 10]\ \mathrm{min}, \tag{13}$$

$$[d_1 \quad d_{0.5} \quad d_0] = [0 \quad 5 \quad 10]\ \mathrm{km}, \tag{14}$$

$$[c_0 \quad c_{0.5} \quad c_1] = [500 \quad 750 \quad 1000]\ \mathrm{m}. \tag{15}$$

The threat-based approach is compared with the task-based approach to sensor management. For both approaches, the trace of the covariance matrix is used as a measure of uncertainty because it is intuitively easier to understand than the KLD. In other words, the task-based approach selects the sensing action that minimizes the expected trace of the target states covariance matrix, but the threat-based approach selects the sensing action that minimizes the expected trace of the target threat covariance matrix.

Assuming that at time $k-1$ the single-target threat θ_{k-1}, conditioned on all observations up to and including time $k-1$, is distributed according to $\theta_{k-1} \sim \mathrm{p}(\theta_{k-1})$, $\theta_{k-1} \in [0,1]$ and that its corresponding variance is $(\sigma_{k-1})^2$, it follows that the index i_k of the sensing mode is given by

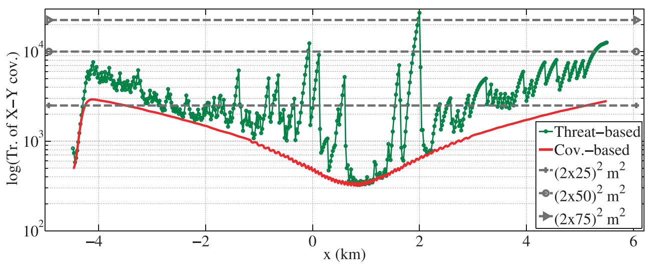
$$i_k = \arg\min_i \left\{ E_{\mathcal{Z}}\left[\left(\sigma_k^{(i)}\right)^2 \right] \right\} \tag{16}$$

and $\sigma_k^{(i)}$ depends on the sensing mode i that is used.

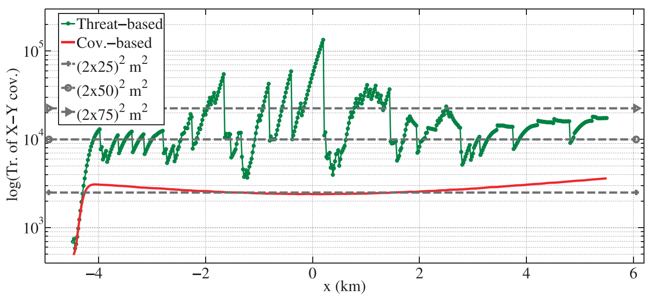
If an analytical expression cannot be found for (16), it can be implemented in a Monte Carlo fashion by sampling from the pdf of the target.

Firstly, it is verified that the aforementioned threat functions are reasonable. Figs. Fig. 5(a) through Fig. 5(c) demonstrate how the mean value of the threat evolves for each target trajectory. As expected, the threat attains its highest value for the incoming target because it both approaches the asset to be protected, i.e. the radar, and also deviates from the shipping lane. The target that remains in the corridor has the lowest threat values because it does not deviate from the shipping lane and eventually moves away from the radar. The threat values of the receding target are somewhere in-between because even though it deviates from the shipping lane, it eventually moves away from the radar. It can also be noticed that the threat level increases when the target approaches the radar or leaves the corridor, as per the used definition of threat. The exact threat levels depend on the chosen weights and points where the individual threat functions become equal to 0, 0.5, and 1.

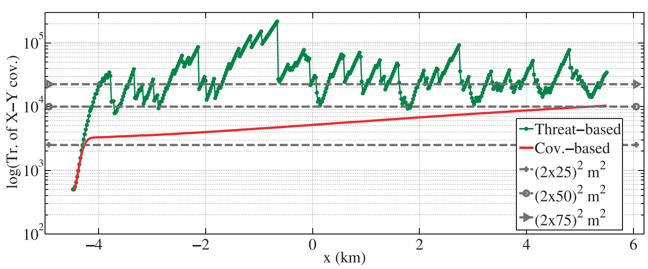
Secondly, we highlight the differences in sensor selection between the threat-based approach and the task-based approach. Figs. Fig. 6(a) through Fig. 6(c) demonstrate how the trace of the covariance matrix of the target $X-Y$ position estimate evolves over time using the two different sensor management approaches. Table I



(a) Incoming target, leaving the corridor (trajectory 1 in Fig. 4).



(b) Target moving in the corridor (trajectory 2 in Fig. 4).



(c) Receding target, leaving the corridor (trajectory 3 in Fig. 4).

Fig. 6. Evolution of trace of $X-Y$ covariance matrix for three different trajectories. Notice that logarithmic scale is used for Y-axis.

demonstrates the sensor selections for the two different approaches along with the expected logarithm of the squared error in threat estimation, the expectation taken with respect to the simulation time. In other words, we examine how the threat-based approach performs in the context of the task-based approach and vice versa.

By comparing Figs. 6(a) through 6(c) with Table I, the first advantage of the threat-based approach can be seen. The two approaches provide comparable threat estimation errors but the threat-based approach uses much less sensor resources; see Table I. A consequence of the lower resource consumption is that the target is tracked with less accuracy, especially when the target is close to the radar and the uncertainty in the threat is minimal. Here it must be pointed out that good tracking accuracy was not the objective of the threat-based approach as opposed to the task-based approach. The threat-based approach has the assumption that the uncertainty in the true threat level of the target is important and that once the uncertainty is low enough the operator will take a proper action. If the tracking accuracy is also of interest, then a corresponding threat function must be (re)defined.

The preference of each sensor management approach for a given sensing mode depends on the geometry of the

TABLE I
Sensor Selection Results and Threat Estimation Squared Error (T.S.E.)

	Threat-based	Task-based
(a) Incoming Target, Leaving the Corridor		
no meas. [selections / Total time]	110/500	0/500
mode 1 [selections / Total time]	138/500	439/500
mode 2 [selections / Total time]	252/500	61/500
E_t[log(T.S.E.)]	−12.01	−11.768
(b) Target Moving in the Corridor		
no meas. [selections / Total time]	161/500	0/500
mode 1 [selections / Total time]	33/500	494/500
mode 2 [selections / Total time]	306/500	6/500
E_t[log(T.S.E.)]	−9.509	−10.263
(c) Receding Target, Leaving the Corridor		
no meas. [selections / Total time]	331/500	0/500
mode 1 [selections / Total time]	67/500	493/500
mode 2 [selections / Total time]	102/500	7/500
E_t[log(T.S.E.)]	−7.898	−8.064

scenario at hand and the specific choice of the measurement noise covariance matrices. For different geometries, different sensing mode preferences have been observed but the threat-based approach always used fewer resources than the task-based approach.

The second advantage of the threat-based approach, which is its flexibility, is demonstrated in the following subsection.

B. Multitarget Example: Radar Beam Pointing in Different Operational Contexts

In the second example, we show that the proposed approach can be used in realistic and challenging problems such as tracking multiple targets using an agile radar beam while taking into account an imperfect detection process. The challenge arises from the combination of two also challenging problems: 1) multiobject filtering under data association uncertainty; and 2) allocating resources among different tasks (i.e., radar time among targets) under different operational contexts (here: asset protection and air traffic control).

Furthermore, it is shown that the proposed approach can be implemented using quantities from a state-of-the-art signal processing algorithm, i.e., a cardinality-balanced multi-Bernoulli (CB-MeMBer) filter; see [31]. A CB-MeMBer filter can in principle take into account contextual information such as occlusion of targets due to obstacles, more targets coming from a specific direction, etc. This can be done by proper definition of the likelihood function and the target birth process for example.

The multi-Bernoulli representation of the posterior density allows direct and accurate state estimates extraction [31], which is crucial for pointing a narrow radar beam. A state estimate is extracted from the estimated multitarget pdf using the marginal multitarget (MaM) estimator, introduced in [32, p. 497]. The MaM estimator first finds the arg max estimate $\hat{N}$ of the number of targets using the estimated cardinality distribution.

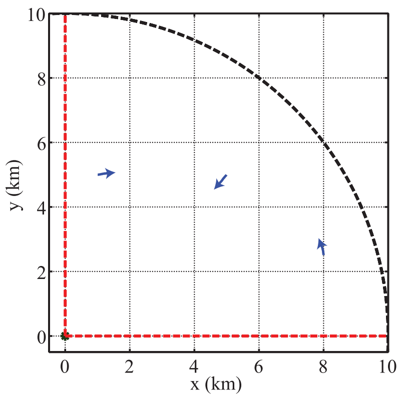


Fig. 7. True trajectories of targets. Radar is located at origin of axes.

Subsequently, an arg max state estimate is extracted from the $\hat{N}$ densities with the highest probability of existence.

Several approaches, both adaptive and naive, are compared with the proposed approach. The naive approaches amount to selecting the beam direction such that all the targets are observed sequentially or at random order. The adaptive approaches, against which the proposed method is compared, are: 1) selecting the action that minimizes the intrinsic uncertainty in the multitarget states pdf, measured by its entropy, see [33]; and 2) selecting the action that maximizes PENT, see [5]. These methods are also presented in the Appendix.

Consider a scenario, shown in Fig. 7, where a phased array radar is tasked with tracking an unknown number of targets. The radar can track targets in the sector defined by [0, 10] km in range and [0, $\pi/2$] rad in bearing using its "pencil" beam.

Three targets are present during the full duration of the scenario, which is 90 time instances. Their initial positions in $x - y$ are [1, 5] km, [5, 5] km, and [8, 2.5] km, respectively. Their initial velocities in $x - y$ are [6, 0] m/s, [–5, –5] m/s, and [0, 7] m/s, respectively. The motion of the targets follows a nearly constant velocity model with $T = 1$ s and $\sigma_x^2 = \sigma_y^2 = 1$ (m/s)^2. All the targets have radar cross-section (RCS) = 10 m^2.

The targets are observed via a radar that provides range and bearing measurements. The measurement noise covariance matrix is $\Sigma_v = \mathrm{diag}[(10\ \mathrm{m})^2, (0.5\ \mathrm{degrees})^2]$.

The radar beam has width of 2 deg without loss due to the target not being on the boresight of the beam. The probability of detecting a target is calculated using the radar equation and the Swerling I model and it is considered zero outside the beam. Depending on the distance between a target and the radar, the probability of detection is in the range of [0.8, 0.9] for the specific trajectories of the targets. Furthermore, false alarms can arise with rate $\kappa = 3.18 \cdot 10^{-5}$ (rad – m)$^{-1}$, i.e., a clutter measurement is received with probability 0.01 at each time instance.

In order to examine the behavior of the sensor management schemes, it is assumed that the CB-MeMBeR filter is initialized with all the correct tracks and one false track. Ideally, the true tracks must be maintained with as good accuracy as possible and the false track should be eliminated. Furthermore, good situation awareness must be achieved, measured by the intrinsic uncertainty in the multitarget threat pdf.

The correct tracks are initialized with $r^{(i)} = 0.8$, with standard deviation of 100 m around the true $x - y$ position and standard deviation of 1 m/s around the true $x - y$ velocities. The false track is initialized with $r^{(i)} = 0.5$, with mean position uniformly random in the sector defined by [1, 9] km and [0.01, 0.9$\pi/2$] rad, standard deviation of 100 m in $x - y$ axes, and $x - y$ velocity uniformly random in [–5, 5] m/s at each Monte Carlo run.

New tracks are initiated from the measurements of the previous time instance that were not assigned to any existing tracks. The newly created tracks are initialized with $r^{(i)} = 0.5$, standard deviation of 100 m round the measured $x - y$ position, and with $x - y$ velocity uniformly random in [–5, 5] m/s. The probability of survival of each target is $p_{S,k} = 0.99$ and tracks with $r^{(i)} < 0.005$ are pruned.

Each Bernoulli component (track) is approximated using 2000 particles and the entropy is evaluated using the 50 nearest neighbors of each particle. The integrals in (18), (20), and (17) are evaluated in a Monte Carlo fashion using particles from the corresponding pdfs. For the random, periodic and PENT sensor management schemes, 100 Monte Carlo simulations were performed. For the entropy-based schemes, 50 Monte Carlo simulations were performed due to computational complexity reasons.

For evaluating the threat, $m_1 = m_2 = 0.5$, $[t_1, t_{0.5}, t_0] =$ [0, 50, 10] min and $[d_1, d_{0.5}, d_0] =$ [0, 7.5, 15] km are used for both the asset protection and air traffic control contexts. In asset protection, the time and range to CPA between each target and the radar is considered, whereas in air traffic control the time and range to CPA between each pair of targets is considered.

Additionally, the fact that $P_D < 1$ and $P_{FA} > 0$ imply that there is uncertainty in the existence/presence of estimated tracks. This leads to corresponding uncertainty in the existence of threat components. For this reason we need to create appropriate models for the multitarget threat. Here, we approximate the multitarget threat pdf as a multi-Bernoulli pdf.

In the example considered here, where a CB-MeMBer filter is used, the multitarget threat RFS variable Θ is a union of N independent Bernoulli random finite sets (RFSs) $\Theta^{(c)}$ with corresponding existence probabilities $r^{(c)} \in [0, 1]$ and probability density $p(\theta^{(c)})$ defined on $\mathcal{T}$ for $c = 1, \ldots, N_c$. Accordingly, Θ is fully described by the corresponding multi-Bernoulli parameter set $\{r^{(c)}, p(\theta^{(c)})\}_{c=1,\ldots,N_c}$, where $p(\theta^{(c)}) := \mathrm{p}(\theta^{(c)}(\mathrm{x})) : \mathrm{x} \sim p^{(c)}(\mathrm{x})$. The multitarget threat Θ has the same cardinality distribution as the multitarget state RFS $\mathbf{X}$, i.e., one threat component per track/target is used.

Therefore, the radar beam direction is given by

$$u_k = \arg \min_u \left[\int H(\Theta|\mathbf{Z})\, g\left(\mathbf{Z}|\mathbf{X}_{k|k-1}, u\right) \delta\mathbf{Z} \right]$$
$$u = \left\{ \mathrm{atan}\left(\hat{y}^j, \hat{x}^j\right) \right\}, \quad \forall j \in [1, \ldots, N] \tag{17}$$

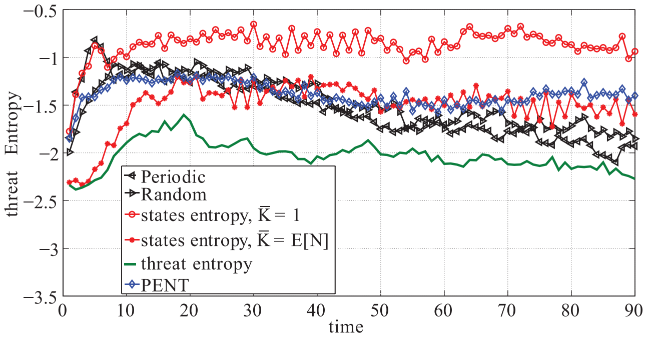


Fig. 8. Asset Protection: Posterior threat entropy, averaged over 100 Monte Carlo runs. Threat-based scheme has best performance, states-based threat scheme has worst performance, and PENT has worse performance than random and periodic schemes in the long run.

where $\mathbf{Z}$ is the set of measurements collected due to pointing the radar beam at direction u given by the arg max estimate $\hat{\mathrm{x}}^{(j)} = [\hat{x}^j, \hat{v}_x^j, \hat{y}^j, \hat{v}_y^j]^{\mathbf{T}}$ of the distribution of component (j), $\mathbf{X}_{k|k-1} = \{\mathrm{x}^{(1)}, \ldots, \mathrm{x}^{(N)}\}$ is the predicted multitarget state at time k, N is the cardinality of $\mathbf{X}_{k|k-1}$, $g(\mathbf{Z}|\mathbf{X}_{k|k-1}, u)$ is the measurement likelihood, and $H(\Theta|\mathbf{Z})$ is the entropy of the updated multitarget threat given a (multitarget) measurement $\mathbf{Z}$. A longer discussion on the entropy of a multi-Bernoulli RFS can be found in Subsection A of the Appendix.

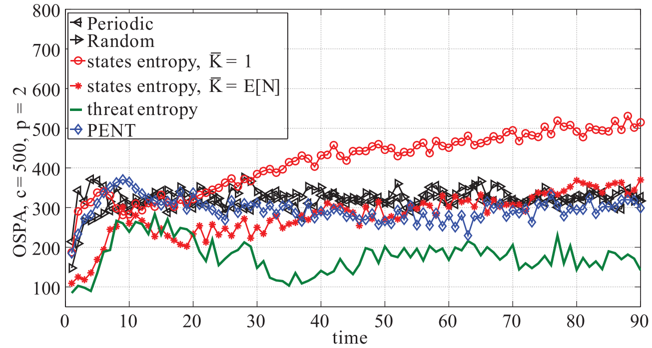
The main difference between the proposed threat-based sensor management and the PENTI scheme is that we explicitly minimize the uncertainty in the multitarget threat pdf whereas in PENTI, the threat level (or tactical significance) of each target is taken into account for modifying the posterior expected number of targets (PENT), which is the quantity to be maximized. Unfortunately, the authors were not able up to this point to implement the PENTI scheme using quantities from a running CB-MeMBer filter.

The sensor management results of each approach are compared both with respect to the resulting uncertainty in the posterior multitarget threat (using the entropy) and with respect to their tracking performance (using the optimal subpattern assignment (OSPA) metric; see [34]). The OSPA metric is evaluated using the true states of the three targets and the MaM estimator.

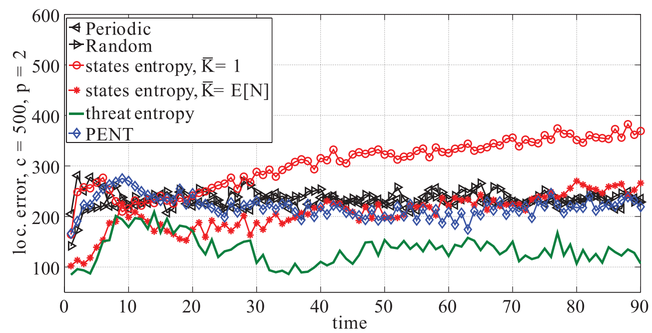
1) *Asset Protection*: Here it is assumed that the operator is tasked with protecting the asset where the radar is located. Therefore, threat is modeled using (6) and (7).

Fig. 8 shows the entropy of the posterior threat pdf, averaged over 100 Monte Carlo simulations. It can be seen that the proposed threat-based scheme outperforms all the other approaches and results in lower uncertainty in the multitarget threat pdf. Interestingly, in this case, the PENT scheme performs worse than the periodic and random schemes in the long run (keeping in mind though that a myopic optimization scheme is used).

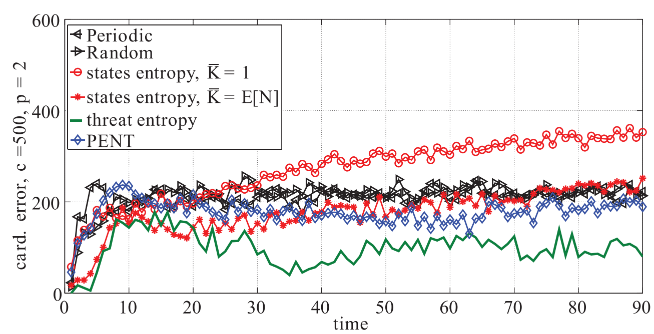
The OSPA metric, averaged over 100 Monte Carlo simulations, and its corresponding components are shown



(a) OSPA metric.



(b) Localization error.



(c) Cardinality error.

Fig. 9. Asset Protection: OSPA metric and its components, averaged over 100 Monte Carlo runs. Threat-based scheme has best performance, states-based threat scheme has worst performance, and PENT has slightly better performance than random and periodic schemes.

in Fig. 9. It can be seen that the proposed threat-based scheme outperforms all other approaches considered here even though that was not the goal of the proposed approach. This result is an unexpected by-product of the proposed method that is worth further research in order to be explained. Interestingly, the scheme based on the entropy of the multitarget states with $\bar{K} = 1$ has the worst performance. The PENT scheme has slightly better performance than the random and periodic schemes, contrary to the results in [35] where it performed worse than choosing a random sensing action (albeit in a different experimental setting). One reason for PENT not performing as well as the proposed approach can be the use of a narrow beam and a myopic optimization scheme that do not allow for observing multiple targets simultaneously or during multiple time steps.

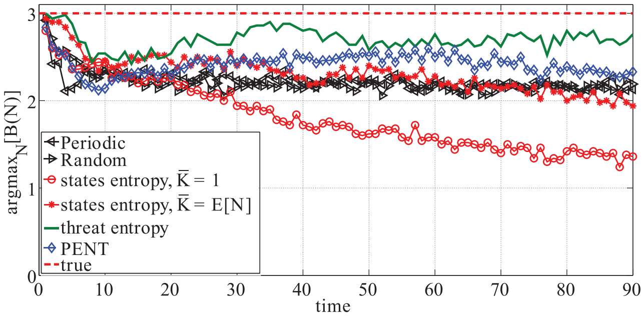


Fig. 10. Asset Protection: arg max estimate of number of targets, averaged over 100 Monte Carlo runs. Threat-based scheme has best performance, states-based threat scheme has worst performance, and PENT has slightly better performance than random and periodic schemes.

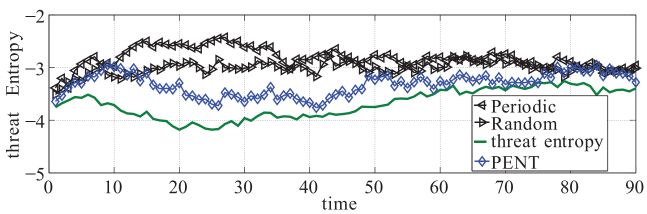


Fig. 11. Air traffic control: Posterior threat entropy, averaged over 100 Monte Carlo runs. Threat-based scheme has best performance.

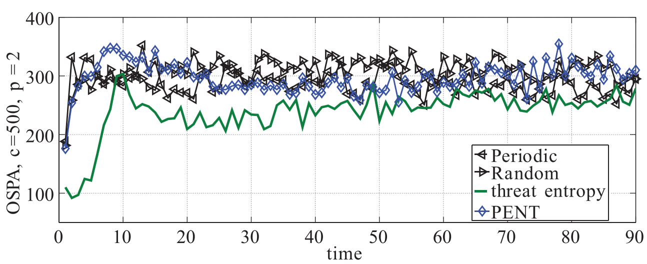


Fig. 12. Air traffic control: OSPA metric averaged over 100 Monte Carlo runs. Threat-based scheme has best performance, states-based threat scheme has worst performance, and PENT has slightly better performance than random and periodic schemes.

Fig. 10 shows the arg max estimate of the number of targets, averaged over 100 Monte Carlo simulations. It can be seen again that an important reason why the proposed threat-based scheme outperforms all other schemes considered here is its superior performance in estimating the correct number of targets.

2) *Air Traffic Control*: Here it is assumed that the operator is tasked with performing air traffic control. Therefore, threat is modeled using (6), (7), and (8) as discussed in Subsection III-B.

Fig. 11 shows the entropy of the posterior threat pdf, averaged over 100 Monte Carlo simulations. It can be seen that the proposed threat-based scheme outperforms all other approaches considered here.

The OSPA metric, averaged over 100 Monte Carlo simulations is shown in Fig. 12. Again, the proposed threat-based scheme outperforms all the other approaches.

Fig. 13 shows the arg max estimate of the number of targets, averaged over 100 Monte Carlo simulations. It can

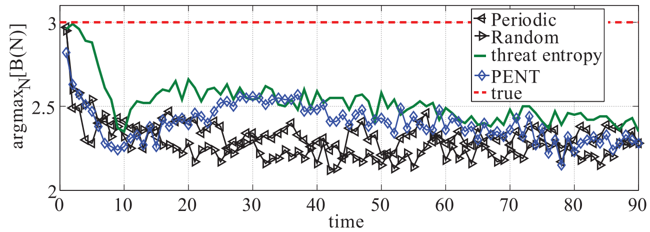


Fig. 13. Air traffic control: arg max estimate of number of targets, averaged over 100 Monte Carlo runs. Threat-based scheme has best performance.

be seen again that an important reason why the proposed threat-based scheme outperforms the other schemes is its superior performance in estimating the correct number of targets.

Videos demonstrating the behavior of the proposed and compared approaches can be found on YouTube; see http://www.youtube.com/playlist?list = PLE5W2H3_7ZUIXALFQgs19NxA7x0EPYvBn. Notice that the videos can only be accessed via the provided link and not by searching YouTube.

In the videos it can be seen that when the entropy of the states' pdf is used then it takes more time for the false tracks to be removed and the existence probabilities of the tracks that correspond to existing targets vary significantly over time. On the other hand, when PENT or the entropy of the threat pdf is used then false tracks are erased faster and the existence probabilities of the tracks that correspond to existing targets do not vary as much.

V. CONCLUSIONS

We have developed a novel approach to sensor management that was inspired by the threat assessment process. The threat-based approach presented shifts the focus from the uncertainty in the target state space (typically 2D/3D position and velocity) to the uncertainty in the threat domain. Accordingly, the threat-based sensor management algorithm chooses the sensing action that minimizes the uncertainty in the threat level of the targets.

The main advantage of this approach is that contrary to the task-based and information- driven approaches, the threat definition can be easily adapted by an operator such that it takes into account what is important at a given operational context, both military and civilian. Furthermore, within this approach, the ability to meaningfully aggregate more than one aspect of threat has been demonstrated.

In principle, this approach can be applied for scheduling a radar beam or selecting waveform parameters. Furthermore, it can be applied to a wide range of scenarios as long as threat can be modeled in the context of the scenario at hand. As a proof of concept, we provided examples both from the defence and from the civilian domain.

The proposed approach was used in a simulated multitarget tracking example and compared with pointing a radar beam based on the entropy of the multitarget density, with PENT, and with periodic and random observation of all targets. The proposed approach outperformed the other schemes in 1) achieving better situation awareness by minimizing the uncertainty in the threat level of all targets; 2) estimating the correct number of targets; and 3) localizing them. The superior performance is achieved at the cost of higher computational load compared with the PENT, periodic, and random schemes.

As future work, the authors are interested in creating threat functions that also take into account contextual, nonmeasurable information. More research is needed in this field in order to explore how threat can be defined mathematically. It is also of interest to implement the PENTI scheme using quantities of a running CB-MeMBer filter. By doing so, two RFS-based schemes that take into account explicitly the threat level (or tactical significance) of targets for selecting the best sensing action, albeit in a different way, can be compared. Moreover, the authors would like to explore the behavior of the considered sensor management criteria when nonmyopic optimization is performed. In this way, better conclusions can be made about the long-term behavior of the considered criteria and potentially better performance can be achieved.

APPENDIX DESCRIPTION OF COMPARED ADAPTIVE SENSOR MANAGEMENT SCHEMES

Here we present the equations and implementations of the adaptive sensor management schemes that are compared with our proposed approach in Subsection IV-B.

A. Information-Driven Sensor Management

We use the conditional entropy as a measure of uncertainty of a pdf in the RFS context. Accordingly, the radar beam is pointed towards direction u_k, given by

$$u_k = \arg\min_u \left[\int H\left(\mathbf{X}_{k|k}|\mathbf{Z}\right) g\left(\mathbf{Z}|\mathbf{X}_{k|k-1}, u\right) \delta\mathbf{Z} \right]$$
$$u = \left\{ \operatorname{atan}\left(\hat{y}^j, \hat{x}^j\right)\right\}, \quad \forall j \in [1, \ldots, N] \tag{18}$$

where $\mathbf{Z}$ is the set of measurements collected due to pointing the radar beam at direction u given by the arg max estimate $\hat{\mathrm{x}}^{(j)} = [\hat{x}^j, \hat{v}_x^j, \hat{y}^j, \hat{v}_y^j]^{\mathbf{T}}$ of the distribution of component (j), $\mathbf{X}_{k|k-1} = \{\mathrm{x}^{(1)}, \ldots, \mathrm{x}^{(N)}\}$ is the predicted multitarget state at time k, N is the cardinality of $\mathbf{X}_{k|k-1}$, $g(\mathbf{Z}|\mathbf{X}_{k|k-1}, u)$ is the measurement likelihood, and $H(\mathbf{X}_{k|k}|\mathbf{Z})$ is the entropy of the updated $\mathbf{X}_{k|k}$ given a (multitarget) measurement $\mathbf{Z}$.

The entropy of some basic RFS pdfs has been calculated in an unpublished paper; see [33]. Equation (17) in [33] is used for calculating the entropy $H(\mathbf{X})$ of a multi-Bernoulli RFS $\mathbf{X} \in \chi$:

$$H(\mathbf{X}) = H(|\mathbf{X}|) + \mathrm{E}\left[H\left(p_n(\mathrm{x})\right)\right] - \mathrm{E}\left[\log\left(|\mathbf{X}|!\right)\right] - \mathrm{E}\left[|\mathbf{X}|\right]\log\left(\bar{K}\right) \tag{19}$$

where:

1) $H(|\mathbf{X}|)$ is the entropy of the cardinality distribution $B(N)$. The cardinality distribution of a multi-Bernoulli RFS is given in [32, p. 369] and the evaluation of its entropy is trivial.

2) $\mathrm{E}[H(p_n(\mathrm{x}))]$ is the expected entropy of the distribution of the Bernoulli components, the expectation taken w.r.t. the cardinality distribution. This term can be calculated by first reconstructing $p_n(\mathrm{x})$ for every possible cardinality $n = 1, \ldots, N$, then calculating each corresponding entropy and finally, calculating $\mathrm{E}[H(p_n(\mathrm{x}))]$. The pdfs $p_n(\mathrm{x})$ can be approximated by properly combining samples drawn from the pdf of each independent Bernoulli component (i). The entropies $H(p_n(\mathrm{x}))$ can be calculated using the sample approximations of the corresponding pdfs and the k-NN method proposed in [36].

3) $\mathrm{E}[\log(|\mathbf{X}|!)]$ is the expected value of the logarithm of the factorial of the cardinality, the expectation taken w.r.t. the cardinality distribution. Its evaluation is also trivial.

4) $\mathrm{E}[|\mathbf{X}|]\log(\bar{K})$ is a term that compensates for the units in the $p_n(x)$. $\bar{K} = K/\alpha$ is a unitless quantity, where K represents the unit that the space is measured and α is the unit of the volume measure of $\mathbf{X}$.

For the entropy of the multitarget states' pdf it is not clear what is the value of $\bar{K}$. Therefore, two values have been used: $\bar{K} = 1$ and $\bar{K} = \mathrm{E}[N]$.

On the other hand, it holds that the single-target threat space $\mathcal{T}$ has volume 1 and that $\bar{K} = 1$ and $\log(\bar{K}) = 0$. Accordingly, the term $\mathrm{E}[|\mathbf{X}|]\log(\bar{K}^n)$ in (19) is equal to zero and can be ignored.

B. PENT-Based Sensor Management

In order to reduce the computational complexity, it is assumed that an ideal set of measurements can be collected [5], i.e., no measurement noise and no false alarms but the probability of detection can be less than one. Given this ideal set of predicted measurements, the sensing action that maximizes the posterior expected number of targets is performed.

When a CB-MeMBer filter is used, the radar beam direction, based on PENT, is given by

$$u_k = \arg\max_u \left[\int \left(\sum_{i=1}^{N(k)} r_{k|k}^{(i)}(\mathbf{Z}) \right) g\left(\mathbf{Z}|\mathbf{X}_{k|k-1}, u\right) \delta\mathbf{Z} \right]$$
$$u = \left\{ \operatorname{atan}\left(\hat{y}^j, \hat{x}^j\right)\right\}, \quad \forall j \in [1, \ldots, N] \tag{20}$$

where $r_{k|k}^{(i)}(\mathbf{Z})$ is the updated probability of existence of component (i).

ACKNOWLEDGMENT

The authors would like to acknowledge Dr. Edson Hiroshi Aoki and Dr. Mélanie Bocquel for their insightful comments.

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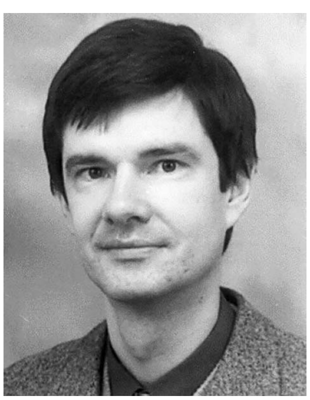

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