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Threat-based sensor management for joint target tracking and classification

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***Abstract*—Joint target tracking and classification is a challenging problem where the class of a target must be estimated in addition to its kinematic states, such as position and velocity. This problem is of special importance both in civilian and in military domain, where target classification plays an important role in the decisions that an operator makes. Moreover, when several sensing options are available for performing joint target tracking and classification then a sensor management problem arises in addition to the joint tracking and classification problem. For addressing this sensor management problem, we propose managing the uncertainty in the threat-level of a target under observation. Since threat is a context-sensitive quantity, it can be defined in different operational contexts both civilian and military. This makes threat-based sensor management for joint classification and tracking a promising alternative to standard sensor management schemes that can be found in the literature. In order to support the latter statement and demonstrate the potential of our idea, we show simulated examples from both domains.**

***Index Terms*—Sensor management, operational risk, threat assessment, target tracking, target classification.**

I. Introduction

In many decision-making problems situation awareness plays a crucial role. Most commonly, good situation awareness is necessary when targets (e.g. aircrafts and vessels) are observed in the context of safety, security, and defense applications. Example scenarios include maritime traffic control, counter-piracy operations, and area surveillance and defence.

Good situation awareness implies having good knowledge about the location and types of targets that are in an area of interest. In order to obtain this knowledge, the problem of joint tracking and classification of targets must be solved.

Joint target target tracking and classification is necessary since the target tracking and classification problems are correlated. If one can estimate correctly the kinematic model of a target then the class of said target can be estimated more easily and more accurately. Similarly, if the class of a target is known then a better/more accurate kinematic model can be used for tracking said target.

Very often different sensors are used for solving these two problems. A surveillance radar is commonly used for observing an area of interest and estimating the kinematic properties, such as position and velocity, of targets in that area. Targets can then be classified using various passive and active systems such as the radar itself, Automatic Identification System (AIS), and cameras. Some targets are co-operative and report their class via a reporting/communication system, e.g. using AIS. In other cases, the reporting system might fail or targets can be non-cooperative, which makes their classification an additional task for the sensors and the operators. After classifying the observed targets, it is possible to use the obtained information (position,velocity, class etc) about these targets in order to make decisions and take proper actions.

When only a radar is available and the observed targets are non-cooperative, it is still possible to use its measurements for solving the joint target tracking and classification problem. In such case, target classification is usually achieved using different kinematic and RCS models for different classes of targets. Some prominent examples from the literature can be found in [1], [2], [3], [4], [5].

The inference part of this joint problem has received a lot of attention but much less research effort has been devoted to sensor control for obtaining improved estimation and classification results. In fact, one can find several publications that address the sensor management problem for target tracking (e.g. [6], [7]) and classification (e.g. [8], [9]) separately but to the best of our knowledge there are no publications that discuss the sensor management problem for joint target tracking and classification, except for [10] where the uncertainty in target class is mentioned but eventually not modeled. When joint target tracking and classification is considered, it can be expected that different sensing options (e.g. waveform parameters) can result in better tracking accuracy at the expense of classification accuracy and vice versa. As a result, the sensor resources must be allocated such that a good trade-off between tracking and classification accuracy is achieved.

In this paper we look at the sensor management problem when joint target tracking and classification is of interest. We explore the behavior of two task-based and information-driven criteria and we propose solving this problem on an higher JDL level, i.e. by performing sensor management such that the uncertainty in the threat-level of a target of interest is managed. Accordingly, we enrich the threat models presented in [11], [12] such that target classification can also be taken into account. We demonstrate our idea using examples taken both from civilian and from defence contexts. Asset protection serves as an example from a defence context, whereas air-traffic-control serves as an example from a civilian context.

Section II discusses the system setup and formulates the joint target tracking and classification problem that we seek to address using sensor management. Section III presents the existing approaches to sensor management based on quantities from a running filter. Section IV presents the proposed threat-based sensor management scheme. Simulated examples are shown and discussed in Section V. Finally, the paper is concluded with Section VI.

II. System setup and problem formulation

The system setup that is considered here is similar to the setup used in [1].

The state vector of a target at time k is denoted by $\mathbf{x}_k \in \mathbb{R}^{n_x}$ and usually comprises position, velocity, and other kinematic variables in 2 or 3 dimensions. The class of a target is a time-invariant and discrete attribute denoted by c and taking values $c \in \{c_i : i = 1, \ldots, n\}$, where i is the class indicator.

Examples of target classes include commercial airplanes, fighters, bombers, UAVs etc. Different classes of targets have different motion envelopes, meaning that targets that belong to the same class have similar maneuverability and speed limits, which are different from those of targets from another class.

The evolution of the state vector can be described by a generic state equation:

$$\mathbf{x}_k = f(\mathbf{x}_{k-1}, c_i) + \mathbf{w}_k(c_i) \tag{1}$$

where $f(\cdot)$ is a possibly non-linear function of state $\mathbf{x}_{k-1}$ and class c_i, $\mathbf{w}_k(c_i)$ is the class-dependent process noise.

The measurement at time k is denoted by $\mathbf{z}_k \in \mathbb{R}^{n_z}$. The measurement is described by the measurement equation:

$$\mathbf{z}_k = h(\mathbf{x}_k, u_k) + \mathbf{v}_{u_k,k} \tag{2}$$

where $h(\cdot)$ is a possibly non-linear function of state $\mathbf{x}_k$ and depends on the sensor (mode) selection u_k, and $\mathbf{v}_{u_k,k}$ is the sensor (mode)- dependent measurement noise. The measurement history up to and including time k is denoted by $\mathbf{Z}_{1:k} = \{\mathbf{z}_1, \ldots, \mathbf{z}_k\}$. The sensor (mode) selection history up to and including time k is denoted by $\mathbf{U}_{1:k} = \{u_1, \ldots, u_k\}$.

The Bayes-optimal target and class pdf $p(\mathbf{x}_k, c_i|\mathbf{Z}_{1:k})$ estimator for the above system has been used in [4], [1], [5], [3], [2]. The prediction step is given by:

$$p(\mathbf{x}_k, c_i|\mathbf{Z}_{1:k-1}) = \int p(\mathbf{x}_k|\mathbf{x}_{k-1}, c_i) \times p(\mathbf{x}_{k-1}, c_i|\mathbf{Z}_{1:k-1}) \,\mathrm{d}\mathbf{x}_{k-1} \tag{3}$$

and the measurement update step is given by

$$p(\mathbf{x}_k, c_i|\mathbf{Z}_{1:k}) = \frac{p(\mathbf{z}_k|\mathbf{x}_k, c_i, \mathbf{Z}_{1:k-1}, u_k) \cdot p(\mathbf{x}_k, c_i|\mathbf{Z}_{1:k-1})}{p(\mathbf{z}_k|\mathbf{Z}_{1:k-1}, u_k)} \tag{4}$$

where $p(\mathbf{z}_k|\mathbf{Z}_{1:k-1}, u_k)$ is a normalizing constant given by

$$p(\mathbf{z}_k|\mathbf{Z}_{1:k-1}, u_k) = \sum_{i=1}^{n} \int p(\mathbf{z}_k|\mathbf{x}_k, c_i, \mathbf{Z}_{1:k-1}, u_k) \times p(\mathbf{x}_k, c_i|\mathbf{Z}_{1:k-1}) \,\mathrm{d}\mathbf{x}_k \tag{5}$$

The posterior class probabilities $P(c_i|\mathbf{Z}_{1:k})$ can be evaluated via marginalization of the updated joint pdf, which results in:

$$P(c_i|\mathbf{Z}_{1:k}) = \frac{\Lambda_k^i}{\sum_{j=1}^{n} \left[\Lambda_k^j \cdot P(c_j|\mathbf{Z}_{1:k-1})\right]} P(c_i|\mathbf{Z}_{1:k-1}) \tag{6}$$

where $\Lambda_k^i = p(\mathbf{z}_k|c_i, \mathbf{Z}_{1:k-1}, u_k)$ is the likelihood function of class i at time k given the sensor selection u_k.

The problem that we want to address in this paper is the selection of the best sensor (or sensing mode) u_k at every time instance k. In other words, we seek to solve at every time instance the following optimization problem

$$u_k = \arg\min_u \{\mathbf{J}(\mathbf{x}_k, \mathbf{Z}_{1:k-1}, \mathbf{z}, u)\} \tag{7}$$

by comparing different criteria $\mathbf{J}(\cdot)$.

III. Sensor management for classification and for tracking

Here we present and discuss shortly different approaches to sensor management that can be found in the literature for taregt tracking and for classification.

A. Sensor management for target tracking

In order to produce Bayes-optimal sensor management results, it has been suggested to optimize quantities that are relevant to the sensing tasks and to the operational goal of a system, hence the name *task-based* sensor management. One of the most common approaches when tracking a target is to select the sensing action such that a covariance-based measure is optimized, see [13], [14]. The trace of the covariance matrix is usually considered when tracking a target using a variant of the Kalman Filter and a sensing action is selected such that its expected value is minimized.

The second most popular Bayes-optimal approach to sensor management is to use information theoretic measures of uncertainty. Accordingly, a sensor manager selects the sensing action that minimizes the conditional or the Rényi entropy of the estimated pdf $p(x_k|\mathbf{Z}_{1:k})$ at time k given by Eq. (8) and (9) respectively.

$$H(X_k|\mathbf{Z}_{1:k}) = -\int p(z_k) \int p(x_k|\mathbf{Z}_{1:k}) \times \log\left(p(x_k|\mathbf{Z}_{1:k})\right) \,\mathrm{d}x_k \,\mathrm{d}z_k \tag{8}$$

$$H_\alpha(X_k|\mathbf{Z}_{1:k}) = -\frac{\int p(z_k) \log\left(\int p^\alpha(x_k|\mathbf{Z}_{1:k}) \,\mathrm{d}x_k\right) \,\mathrm{d}z_k}{\alpha - 1} \tag{9}$$

where X_k is a random variable denoting the state at time k, (x_k, z_k) are the state and measurement realizations at time k, and $\alpha \in (0, 1)$.

Another popular information-theoretic criterion is the Kullback-Leibler divergence (KLD), presented in [15], [16] and given by Eq. (10).

$$D\left[p(X_k|Z_k)||p(X_k)\right] = \int p(x_k|z_k)\log\left(\frac{p(x_k|z_k)}{p(x_k)}\right)\mathrm{d}x_k \tag{10}$$

where $p(X_k)$ denotes the predicted pdf before the measurement update step.

In this paper we use the trace of the covariance matrix and the conditional entropy as measures of uncertainty in a pdf. We choose the conditional entropy instead of KLD because the conditional entropy is easier to implement than the KLD, especially in light of our proposed approach that is discussed in the following section.

B. Sensor management for target classification

Sensor management for target classification is mostly related to radar waveform parameter selection such that the RCS (or scattering characteristics) and/or the kinematic properties of a target can be estimated accurately. Typical examples include [8], [9].

Both publications formulate the target classification problem as a multiple hypothesis testing problem and propose sensor management schemes in this context. In both papers information theoretic notions of uncertainty are used for selecting the best waveform parameters and compared to selecting a waveform such that the SNR at the output of the receiver matched filter is maximized or to a waterfilling approach.

IV. Threat-based sensor management

As it can be seen in the previous section, sensor management is considered separately for tracking and for classification in the literature. This separation can create problems when joint classification and tracking is of interest. Using sensor settings that are optimal for tracking might result in poor classification accuracy and vice versa. Moreover, in both problems the proposed criteria do not take into account the operational context but rather focus on the estimation/classification accuracy. In practice, a different tracking versus classification accuracy trade-off might be optimal in different operational contexts. For example, classification accuracy might be more important in a military operation whereas tracking accuracy might be more important in an ai-traffic-control scenario.

As an alternative to the sensor management approaches presented in the previous section, we propose managing the uncertainty in higher level quantities, such as the threat level of a target. A longer discussion about this approach can be found in [12], [11].

According to the proposed method, we first evaluate the threat pdf of a target and then we manage the uncertainty in the threat pdf. The motivation behind this approach is that operational decisions are usually based on the results of the threat assessment process. If there is low uncertainty in the threat-level of targets then better decisions can be made and with higher confidence in them.

In this paper we use the same threat definitions as in [12]. For the sake of completeness we present these threat definitions here.

From the defense domain, asset protection is considered. Accordingly, the threat that is posed by a target i to asset j depends on how close and how fast target i can come to asset j. These are measured by the time and range to closest point of approach (CPA), which for a target i and an asset j with corresponding state vectors $\mathbf{x}^{(i)} = [x^{(i)} \quad v_x^{(i)} \quad y^{(i)} \quad v_y^{(i)}]^\intercal$ and $\mathbf{x}^{(j)} = [x^{(j)} \quad v_x^{(j)} \quad y^{(j)} \quad v_y^{(j)}]^\intercal$ are given by:

$$t_{CPA}^{ij} = -\frac{\Delta_x^{ij}\Delta_{v_x}^{ij} + \Delta_y^{ij}\Delta_{v_y}^{ij}}{\sqrt{\left(\Delta_{v_x}^{ij}\right)^2 + \left(\Delta_{v_y}^{ij}\right)^2}} \tag{11}$$

$$d_{CPA}^{ij} = \sqrt{\left(\Delta_x^{ij} + t_{CPA}^{ij}\Delta_{v_x}^{ij}\right)^2 + \left(\Delta_y^{ij} + t_{CPA}^{ij}\Delta_{v_y}^{ij}\right)^2} \tag{12}$$

where

$$\Delta_{\text{pos}}^{ij} = [\Delta_x^{ij} \quad \Delta_y^{ij}]^\intercal = [x^{(i)} \quad y^{(i)}]^\intercal - [x^{(j)} \quad y^{(j)}]^\intercal \tag{13}$$

$$\Delta_{\text{vel}}^{ij} = [\Delta_{v_x}^{ij} \quad \Delta_{v_y}^{ij}]^\intercal = [v_x^{(i)} \quad v_y^{(i)}]^\intercal - [v_x^{(j)} \quad v_y^{(j)}]^\intercal \tag{14}$$

In order to move from the time and range domain to the single-target threat domain $\mathcal{T} = [0, 1]$, a sigmoid function can be utilized for example[1]:

$$\theta_t\left(\mathbf{x}^{(i)};\mathbf{x}^{(j)}\right) = \begin{cases} 1 & , |t_{CPA}^{ij}| \leq t_1 \\ 1 - 2\left(\frac{|t_{CPA}^{ij}| - t_1}{t_0 - t_1}\right)^2 & , t_1 < |t_{CPA}^{ij}| \leq t_{0.5} \\ 2\left(\frac{|t_{CPA}^{ij}| - t_0}{t_0 - t_1}\right)^2 & , t_{0.5} < |t_{CPA}^{ij}| \leq t_0 \\ 0 & , t_0 < |t_{CPA}^{ij}| \end{cases} \tag{15}$$

$$\theta_d\left(\mathbf{x}^{(i)};\mathbf{x}^{(j)}\right) = \begin{cases} 1 & , d_{CPA} \leq d_1 \\ 1 - 2\left(\frac{d_{CPA}^{ij} - d_1}{d_0 - d_1}\right)^2 & , d_1 < d_{CPA}^{ij} \leq d_{0.5} \\ 2\left(\frac{d_{CPA}^{ij} - d_0}{d_0 - d_1}\right)^2 & , d_{0.5} < d_{CPA}^{ij} \leq d_0 \\ 0 & , d_0 < d_{CPA}^{ij} \end{cases} \tag{16}$$

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.

Since both time and range to CPA have been mapped to the same domain, i.e. threat, it is meaningful to aggregate these aspects of threat using a weighted sum and eventually evaluate the threat level of a target i with respect to asset j:

$$\theta\left(\mathbf{x}^{(i)};\mathbf{x}^{(j)}\right) = m_t\theta_t\left(\mathbf{x}^{(i)};\mathbf{x}^{(j)}\right) + m_d\theta_d\left(\mathbf{x}^{(i)};\mathbf{x}^{(j)}\right) \tag{17}$$

where m_i is the weight assigned by the operator to $\theta_i\left(\mathbf{x}^{(i)};\mathbf{x}^{(j)}\right)$ such that $m_t + m_d = 1$. In this way, we have

[1]The specific choice of sigmoid functions is only for demonstration purposes. Any other convenient function could be used by the system designer and the operator.

simplified what would have been a two-objective optimization problem to a simpler but still meaningful single objective problem that consists of the weighted sum of the two aspects of threat.

From the civilian domain, air traffic control is considered. Accordingly, threat is now defined by how close and how fast two aircrafts i, j can come to each other. In this case, the notions of time and range to CPA can be utilized again. The difference is that time and range to CPA are now evaluated among all pairs of targets (i, j), where $i, j = 1, \ldots, N$ and $i \neq j$ instead of between each target and an asset. From the $N-1$ different threat values for a target i, the threat value $\theta^*\left(\mathbf{x}^{(i)}\right)$ is selected such that:

$$\theta^*\left(\mathbf{x}^{(i)}\right) := \theta\left(\mathbf{x}^{(i)}; \mathbf{x}^{(j^*(i))}\right) \tag{18}$$

$$\text{where } j^*(i) = \arg\max_{j(\ldots)} \hat{\theta}\left(\mathbf{x}^{(i)}; \mathbf{x}^{(j)}\right)$$

$$\forall i, j \in [1, \ldots, N],\ i \neq j \tag{19}$$

$$\text{with } \widehat{\theta}(\cdot) = \int \theta(\cdot) p\left(\theta(\cdot)\right)\, \mathrm{d}\theta(\cdot) \tag{20}$$

and N is the number of targets in the scenario. The mean threat $\hat{\theta}\left(\mathbf{x}^{(i)}; \mathbf{x}^{(j)}\right)$ can be evaluated in a Monte Carlo fashion using samples from the estimated single targets pdfs $p^{(i)}(\mathbf{x}^{(i)}), p^{(j)}(\mathbf{x}^{(j)})$.

According to the threat definitions described above, it is necessary to specify the time and range to CPA for different target classes in different operational contexts. This leads to class-conditional threat definitions and eventually to multimodal threat pdfs, where the modes represent the target classes considered in a specific context. In other words, the estimated threat pdf is a sum of class-conditional pdfs and each class-conditional pdf represents the threat of the corresponding target class.

Let us consider an asset protection context. A fighter would have a different threat-level than an airliner at the same distance. This is reflected by the different resulting threat levels for a given time and range to CPA with respect to an asset to be protected. Therefore, the time and range to CPA values $t_1 < t_{0.5} < t_0$ and $d_1 < d_{0.5} < d_0$ must be defined for each target class that is of interest in a specific operational context and they will lead to class-conditional threat definitions.

For quantifying the uncertainty in the threat pdf, we select measures of uncertainty from the ones described in Section III. The key difference is that now the uncertainty in the threat pdf is managed instead of the uncertainty in the states' pdf. Because of this change of focus, the operational context is taken explicitly into account in the sensor (mode) selection process.

V. Simulated examples

In order to demonstrate the behavior of the compared sensor management schemes and demonstrate the feasibility of our proposed approach, we adopt and expand the experimental settings of [1]. We seek to track and classify a target denoted as *Aircraft A* in Fig. 1. *Aircraft A* can belong to one of three possible classes: fighter, bomber, or airliner. The duration of the scenario is 80 scans and one scan is performed every 3 seconds.

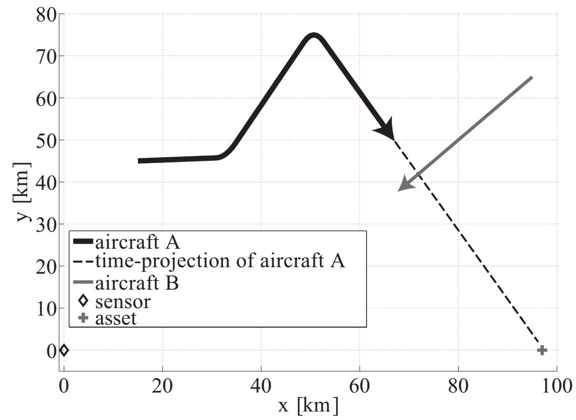

Fig. 1. The trajectory of the target to be tracked (aircraft A), a target (aircraft B) that might collide with the target to be tracked, and an asset to be defended. The sensor is at the origin of the axes.

The trajectory of *Aircraft A*, the true class (fighter), and the filters that are used for tracking and classifying *Aircraft A* in this paper are the same as in [1], i.e. an EKF for airliner class, an IMM-EKF with 5 modes for bomber class, and an IMM-EKF with 13 modes for fighter class. The 5 modes used for bomber class correspond to 0g acceleration in both axes and to combinations of 0 and ± 2g acceleration in x and y axes. The 13 modes used for fighter class include the 5 modes used for bomber class plus combinations of ± 2g accelerations in both axes plus acceleration of 0g and ± 4g in each axis. These modes are shown in Fig. 3 in [1].

Aircraft A moves according to a constant velocity motion model until scan 25. Between scan 26 and 31 *Aircraft A* performs a turn with acceleration $a_y = 2.1$ g, which can only be performed by a bomber or a fighter according to the chosen kinematic models. Then it moves again with constant velocity until scan 52. Between scan 53 and 58 *Aircraft A* performs a turn with acceleration $a_y = -4.2$ g, which can only be performed by a fighter. The second turn reveals the true class of *Aircraft A*, which is a fighter.

The difference from [1] is that here a sensor management aspect is introduced: a sensor with two sensing modes is used and we need to select the best sensing mode at each time instance for observing *Aircraft A*. The first sensing mode can only measure the position of *Aircraft A* and has the following measurement pdf:

$$p_{pos}(\mathbf{z}_k | \mathbf{x}_k, c_i, \mathbf{Z}_{1:k-1}) = \mathcal{N}(\mathbf{z}_k; \mathbf{x}_k, \Sigma_{pos}) \tag{21}$$

where $\Sigma_{pos} = \text{diag}[100^2\ (\text{m})^2, 0, 100^2\ (\text{m})^2, 0]$. The second sensing mode can only measure the velocity of *Aircraft A* and has the following measurement pdf:

$$p_{vel}(\mathbf{z}_k | \mathbf{x}_k, c_i, \mathbf{Z}_{1:k-1}) = \mathcal{N}(\mathbf{z}_k; \mathbf{x}_k, \Sigma_{vel}) \tag{22}$$

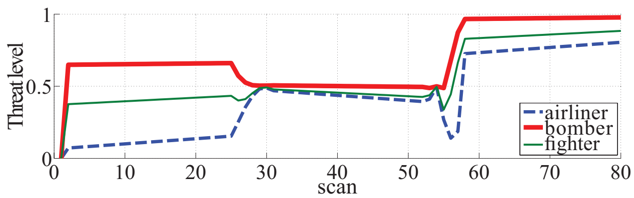

Fig. 2. Threat-levels of considered target classes when asset-protection is performed. Note that the bomber class has the highest overall threat-levels followed by fighter class because these two classes are considered the most dangerous. Naturally, the airliner class has the lowest threat levels because such an attack is assumed highly unlikely.

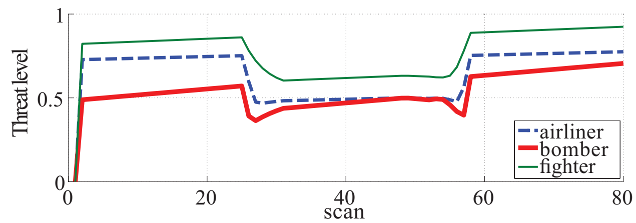

Fig. 3. Threat-levels of considered target classes when air traffic control is performed. Note that the airliner class has the highest overall threat-levels because prevention of collisions is of interest. The second highest threat levels are attained by the fighter class because such attacks might occur. The lowest threat levels are attained by the bomber class because such collisions are assumed highly unlikely.

where $\Sigma_{vel} = \text{diag}[0, 10^2\ (\text{m/s})^2, 0, 10^2\ (\text{m/s})^2]$.

It is assumed that when the sensor operates in defence mode then the measurement collection must be optimized for asset protection. The asset to be protected is located at $[0, 97]$ km, as shown in Fig. 1. In this operational context, the corresponding threat definitions from Section IV are used.

On the other hand, when the sensor operates in civilian mode then the measurement collection must be optimized for performing air traffic control. Here, for simplicity reasons, collision between *Aircraft A* and only one other aircraft, namely *Aircraft B* in Fig. 1, is considered. In this operational context, the corresponding threat definition from Section IV is used.

For each target class and for each operational context, we have selected $t_1 < t_{0.5} < t_0$ and $d_1 < d_{0.5} < d_0$ such that the evolution of threat-level for each potential class of *Aircraft A* for the given trajectory is as shown in Fig. 2 and 3.

Figure 2 shows that the most threatening target class in an asset-protection scenario is the bomber class. The least threatening target class is the airliner class. The threat-levels for the fighter class are in-between the levels of the other two classes. The exact threat-levels can be modeled with the help of an expert and here reasonable assumptions have been made.

Similarly, Fig. 3 shows that the most threatening target class in an air traffic control scenario is the airliner class because we want to prevent collisions among commercial aircrafts. The least threatening target class is the bomber class. The threat-levels for the fighter class are in-between the levels of the other two classes. Once again, here reasonable assumptions about the threat-levels of each class have been made.

A common denominator in both Fig. 2 and 3 is that the threat level of *Aircraft A* increases as it approaches *Aircraft B* or the asset. Similarly, the threat level of *Aircraft A* decreases as it moves away from *Aircraft B* or the asset.

The proposed criteria are

A) minimize the expected variance $\sigma^2_{\hat{\theta},k|k}(\cdot)$ of the mixed threat-level estimate $\hat{\theta}$, i.e.

$$\mathbf{J}_A(\cdot) = \mathrm{E}_{\mathcal{Z}}\left\{\sigma^2_{\hat{\theta},k|k}(\theta, \mathbf{Z}_{1:k-1}, \mathbf{z}, u)\right\} \tag{23}$$

B) minimize the conditional entropy of the posterior threat pdf, i.e.

$$\mathbf{J}_B(\cdot) = \mathrm{E}_{\mathcal{Z}}\{H(p(\theta_k|\mathbf{Z}_{1:k-1}, \mathbf{z}, u))\} \tag{24}$$

The following criteria are compared to the proposed criteria for selecting the best sensing mode:

1) minimize the expected trace of the covariance matrix of the mixed state estimate produced by mixing the outputs of the running filters, i.e.

$$\mathbf{J}_1(\cdot) = \mathrm{E}_{\mathcal{Z}}\left\{\mathrm{tr}\left[\Sigma_{k|k}(\hat{\mathbf{x}}_{k|k-1}, \mathbf{Z}_{1:k-1}, \mathbf{z}, u)\right]\right\} \tag{25}$$

where $\Sigma_{k|k}(\cdot)$ is the covariance matrix of $\hat{\mathbf{x}}_{k|k-1}$, updated with a measurement $\mathbf{z}$ that resulted from using mode $u \in \{pos, vel\}$;

2) minimize the conditional entropy of the posterior pdf given by the mixed estimate and its covariance matrix (i.e. the posterior pdf is approximated as Gaussian pdf) produced by mixing the outputs of the running filters, i.e.

$$\mathbf{J}_2(\cdot) = \mathrm{E}_{\mathcal{Z}}\{H(\mathcal{N}(\hat{\mathbf{x}}_{k|k-1}(\mathbf{Z}_{1:k-1}, \mathbf{z}, u), \Sigma_{k|k}(\hat{\mathbf{x}}_{k|k-1}, \mathbf{Z}_{1:k-1}, \mathbf{z}, u)))\} \tag{26}$$

3) minimize the conditional entropy of the class pdf, i.e.

$$\mathbf{J}_3(\cdot) = \mathrm{E}_{\mathcal{Z}}\{H(p(c|\mathbf{Z}_{1:k-1}, \mathbf{z}, u))\} \tag{27}$$

The mixed estimate and its covariance matrix, as outputs of an IMM-(E)KF filter, are described in standard textbooks, see [17]. For implementing criteria 1 and 2, we mix the outputs of the three filters using the same formulas as when an IMM is used but instead of mode probabilities we use the evaluated class probabilities. For all criteria we have performed 100 Monte Carlo runs in order to compare their resulting classification and tracking accuracy.

Table I summarizes the obtained classification and tracking accuracy results. In Table I, classification accuracy is defined as the percentage of Monte Carlo runs in which the class with highest probability is the correct one (i.e. fighter) at the end of the scenario. It can be seen that in both contexts Criterion 2 results always in correct classification of *Aircraft A* at the expense of position accuracy. Criterion 1 results always in the best position accuracy at the expense of classification accuracy. Criteria A and B achieve a trade-off among classification and tracking accuracy. It can also be seen that the classification accuracy is highly correlated with the velocity estimation accuracy because classification is performed purely based on

TABLE I
CLASSIFICATION AND TRACKING ACCURACY RESULTS

Context	Criterion	Classif. accuracy [%]	RMS pos. error [m]	RMS vel. error [m/s]
Asset protection	A	89	1324	23.4
	B	79	812	45.5
	1	66	722	58.5
	2	100	1503	14.4
	3	92	798	41
Air traffic control	A	66	990	24.9
	B	80	837	42.6
	1	64	718	56.9
	2	100	1469	14.5
	3	89	816	42.4

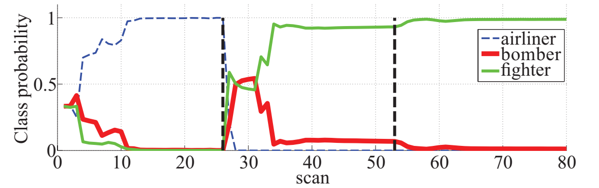

Fig. 4. Estimated target class probabilities in the asset protection context when Criterion A is used.

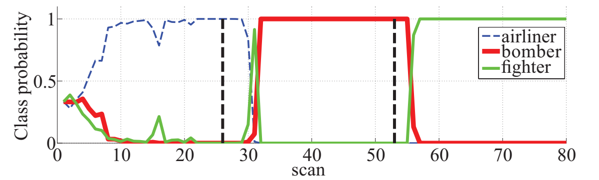

Fig. 5. Estimated target class probabilities in the asset protection context when Criterion B is used.

the maneuverability of *Aircraft A*. Criterion 3 has similar performance to Criterion B.

First, we discuss the behavior of Criterion 1, which results in the best position accuracy among the compared criteria. Criterion 1 almost always chooses the first sensing mode, i.e. it chooses to perform position measurements in 98.3% of scans in both operational contexts. This explains its good localization accuracy and also why it has so poor classification and velocity estimation accuracy.

Secondly, we discuss the behavior of Criterion 2, which results the worse position accuracy among the compared criteria. These results can be explained by the sensor mode selection behavior of Criterion 2. It turns out that Criterion 2 always chooses the second sensing mode, i.e. it always chooses to perform velocity measurements. As a consequence, it manages to always classify the target correctly because the classes are defined purely based on the velocity of targets in each class. This behavior also explains its poor localization accuracy.

Criteria A and B make a compromise among classification and tracking accuracy. This is achieved by utilizing both sensing modes during the duration of the scenario and according to the operational context. In asset protection, criterion A performs a position measurement in 19.6% of scans and criterion B in 65.9% of scans. On the other hand, in air traffic control, criterion A performs a position measurement in 18.8% of scans and criterion B in 60% of scans. The resulting accuracy trade-off depends on the operational context and the threat models that are chosen. Furthermore, this trade-off is achieved without any ad-hoc solutions, such as forcing a percentage of specific sensor mode selections.

Finally, criterion 3 also makes a compromise among classification and tracking accuracy. In fact criterion 3 has very good classification and localization accuracy at the expense of velocity accuracy. It utilizes both sensing modes during the duration of the scenario but it does not adapt to the operational context. In asset protection it performs a position measurement 50.2% of the scans and in air-traffic-control 50.7% of the scans.

Figures 4 to 8 show the estimated target class probabilities from a Monte Carlo run for all the criteria. These figures give a visual impression of the classification accuracy results of the compared criteria in the asset protection context, as discussed earlier. In this example all criteria manage to classify the target correctly at the end of the scenario, after the maneuver that reveals the true class of the target.

Figures 9 to 13 show the estimated target trajectories from a Monte Carlo run for all the criteria in the asset protection context. Here it can be seen that Criterion 1 has the best position accuracy performance, Criterion 2 has the worst position accuracy performance, and the performance of Criteria A and B is somewhere in between the performances of the previous two criteria.

Figures 14 to 18 show the estimated target velocities from a Monte Carlo run for all the criteria in the asset protec-

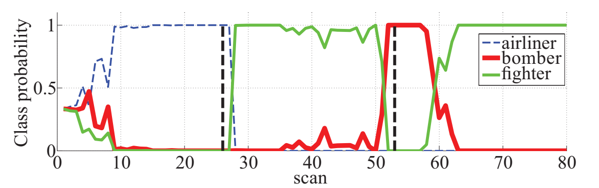

Fig. 6. Estimated target class probabilities in the asset protection context when Criterion 1 is used.

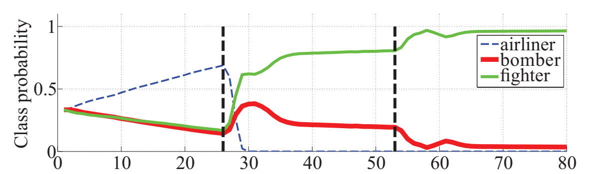

Fig. 7. Estimated target class probabilities in the asset protection context when Criterion 2 is used.

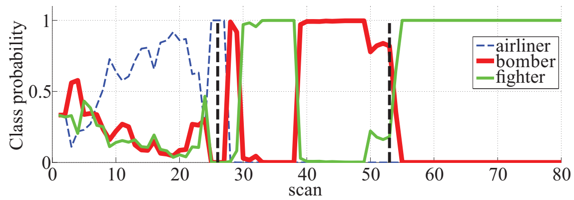

Fig. 8. Estimated target class probabilities in the asset protection context when Criterion 3 is used.

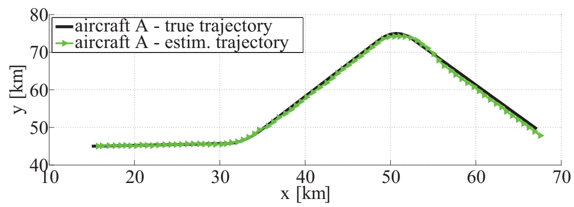

Fig. 9. Estimated target trajectories in the asset protection context when Criterion A is used.

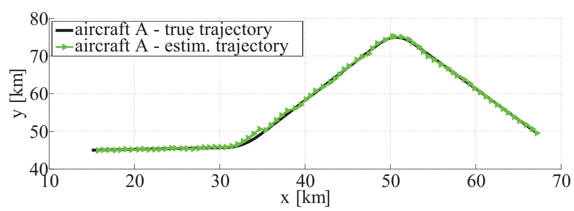

Fig. 10. Estimated target trajectories in the asset protection context when Criterion B is used.

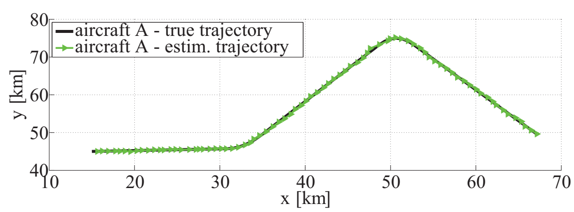

Fig. 11. Estimated target trajectories in the asset protection context when Criterion 1 is used.

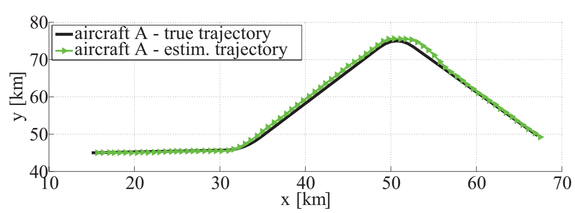

Fig. 12. Estimated target trajectories in the asset protection context when Criterion 2 is used.

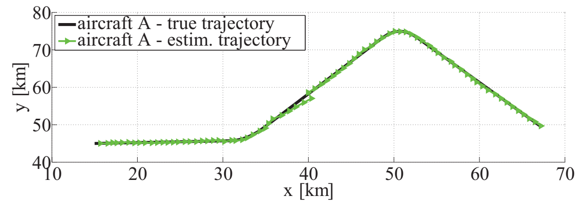

Fig. 13. Estimated target trajectories in the asset protection context when Criterion 3 is used.

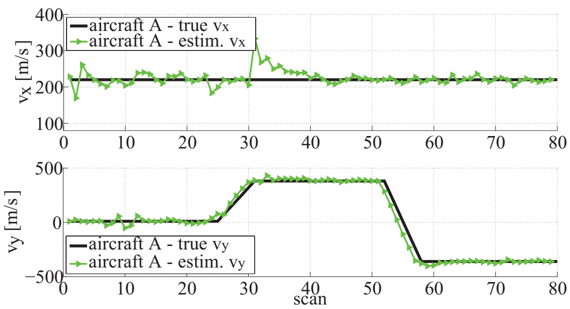

Fig. 14. Estimated target velocities in the asset protection context when Criterion A is used.

tion context. These figures demonstrate why each criterion achieves its corresponding classification accuracy, which is highly correlated with the velocity estimation accuracy in this experimental setting.

VI. Conclusions

The sensor selection problem was considered in the context of joint target tracking and classification. Standard approaches to sensor management that are proposed in the literature were compared to a newly developed method by the authors, i.e. threat-based sensor management. Via simulated examples it was shown that the standard approaches focus either only on localizing the target with high accuracy or only on classifying it with high accuracy. On the other hand, the proposed method results in sensor control that balances the tasks of tracking and classification. The exact trade-off among localization and classification performance depends on the experimental

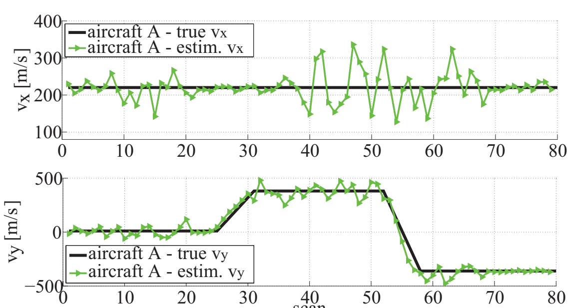

Fig. 15. Estimated target velocities in the asset protection context when Criterion B is used.

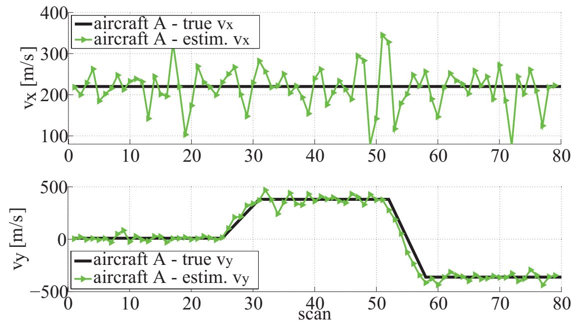

Fig. 16. Estimated target velocities in the asset protection context when Criterion 1 is used.

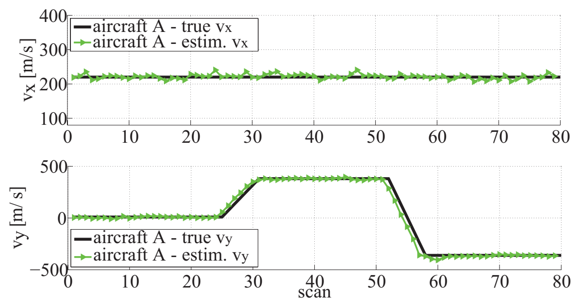

Fig. 17. Estimated target velocities in the asset protection context when Criterion 2 is used.

settings, the operational context, and the threat models that are chosen.

In this paper we present a first step towards a complete system that includes target search, tracking, classification, and sensor management. To confirm that this is the right direction, more research and simulations are needed, especially towards threat definitions and the performance of such a system. In fact, threat could be part of a value metric that includes more components in order characterize targets.

Furthermore, the processing time requirements of such system are expected to pose an added challenge when implementing it.

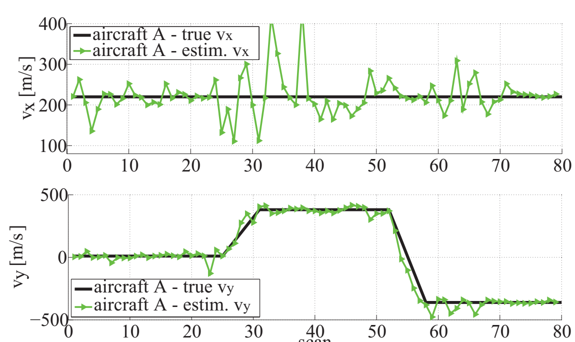

Fig. 18. Estimated target velocities in the asset protection context when Criterion 3 is used.

Acknowledgments

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