Multiresolution EO/IR Target Tracking and Identification

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Abstract – *Simultaneous target tracking and identification through feature association, attribute matching, or blob analysis is dependent on spatio-temporal measurements. Improved track maintenance should be achievable by maintaining coarse sensor resolutions on maneuvering targets and utilizing finer sensor resolutions to resolve closely-spaced targets. There are inherent optimal resolutions for sensors and restricted altitudes that constrain operational performance that a sensor manager must optimize for both wide-area surveillance and precision tracking. The advent of better optics, coordinated sensor management, and fusion strategies provide an opportunity to enhance simultaneous tracking and identification algorithms. We investigate utilizing electro-optical (EO) and Infrared (IR) sensors operating at various resolutions to optimize target tracking and identification. We use a target-dense maneuvering scenario to highlight the performance gains with the Multiresolution EO/IR data association (MEIDA) algorithm in tracking crossing targets.*

Keywords: *Multiresolution, EO/IR, JBPDAF, fusion, ATR*

1 Introduction

The problem of multitarget tracking and identification (ID) is a subset of sensor fusion, which includes filtering, estimation, and prediction. One of the prominent tracking algorithms is the Joint Probability Data Association Filter (JPDAF) [1]. This algorithm seeks to track a set of objects from only positional information, but improvements are underway to use signal-detection analysis to track an object based on the highest signal return [2]. One way to enhance data association is to use EO/IR target attributes to mitigate clutter [3 - 7]. To further enhance the capabilities of the JPDAF algorithm, it would be useful for a sensor to not only get the position of the target, but also the target identity. However, a true identity might not be known, so believable measurements must be used. A combined track and ID algorithm can improve track quality, mitigate clutter confusion, and enhance target ID.
Kinematic and ID measurements can detect, track, and classify targets of interest. The ultimate objective of the tracker includes identifying targets as they move through space. In a dynamic and uncertain environment, the tracker must associate the correct target to the position measurements. All neighbors data association algorithms [1, 8] calculate *a posteriori* probabilities of allocating the position measurements to candidate potential targets. Likewise, other multisensor multiplatform fusion algorithms identify targets from multiple look sequences of sensor data [9]. The merging of these algorithms can be accomplished by investigating the mathematics of the algorithms. Track fusion uses kinematic measurements and ID fusion uses target-feature measurements to update state matrices. We seek to simultaneously track and identify targets by utilizing the merits of data association from multilevel data associations. The *Joint-Belief Probabilistic Data Association* (JBPDA) algorithm using Bayesian and Dempster-Shafer updates was proposed [10]. Similar methodologies include DSm tracking [11].

Target tracking and ID utilizes both kinematic and target features to track targets. Many tracking algorithms either use kinematic information or track features to separate closely spaced targets. A promising strategy is to use the appropriate sensor resolution for the target movement context. To determine the coarse information, we can utilize sensors at low resolutions to obtain the length-to-width ratio of the target. High resolution sensors capture the feature information used to identify the target. In either coarse or fine resolution, three models are necessary (1) target dynamics, (2) target identification, and (3) sensor. The target dynamics include such models as constant velocity or constant turn (which is utilized in an *Interactive Multiple Model* [IMM] – [1, 8, 12]) and a move-stop-move analysis. Target ID models assist in the measurement-to-track association (i.e. EO/IR sensors, shown in Figure 1). Sensor models include the resolution and target movement. All three can update the pose estimate of the target for predicting the next location. Assuming the sensors have a fixed sampling rate, finer resolutions would help resolve interacting targets while decreasing wide area surveillance. Obviously, there are more pixels on target when the sensor is in high resolution.

Figure 1. (a) EO image and (B) IR image of targets.

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14. ABSTRACT

Abstract – *Simultaneous target tracking and identification through feature association, attribute matching, or blob analysis is dependent on spatio-temporal measurements. Improved track maintenance should be achievable by maintaining coarse sensor resolutions on maneuvering targets and utilizing finer sensor resolutions to resolve closely-spaced targets. There are inherent optimal resolutions for sensors and restricted altitudes that constrain operational performance that a sensor manager must optimize for both wide-area surveillance and precision tracking. The advent of better optics, coordinated sensor management, and fusion strategies provide an opportunity to enhance simultaneous tracking and identification algorithms. We investigate utilizing electro-optical (EO) and Infrared (IR) sensors operating at various resolutions to optimize target tracking and identification. We use a target-dense maneuvering scenario to highlight the performance gains with the Multiresolution EO/IR data association (MEIDA) algorithm in tracking crossing targets.*

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One example is having an EO/IR platform where analysis has been applied to target recognition [13, 14, 15]. We would want the EO to capture targets in good lighting conditions and IR to capture thermal images at night. An IR imager can be used at all times of the day, albeit, the performance may degrade during short thermal cross-over periods in the morning and evening. We would want a fine resolution video sensor on closely spaced targets and a coarse resolution on separated targets. To determine the tradeoffs of track filters, we can use a Markov weighting to determine which sensor mode and resolution, which target dynamic and speed model, and what fusion strategy for pose updates.

Many tracking algorithms incorporate ID information, either using the position to locate and detect the target [7], use kinematic information to facilitate target recognition [17] , and an intersection of kinematic and ID information [10, 16]. Also, there are multiresolution algorithms such as using wavelets [9]. To facilitate a pragmatic use of resolution capabilities, it would be desirable to use low resolution for wide area surveillance and high resolution to discern closely space objects.

In data association tracking approaches, typical tracking is provided through position measurements. The problem is that the tracker must isolate the target of interest from the cluttered position measurements. If position measurement information is dense, the tracker can make an incorrect assignment of the position measurements to target tracks. As an example, Figure 2 below shows a case in which the position measurements cause the tracker to get confused. In this case, object 1's and object 2's position measurements fall within the kinematic gates of both objects.

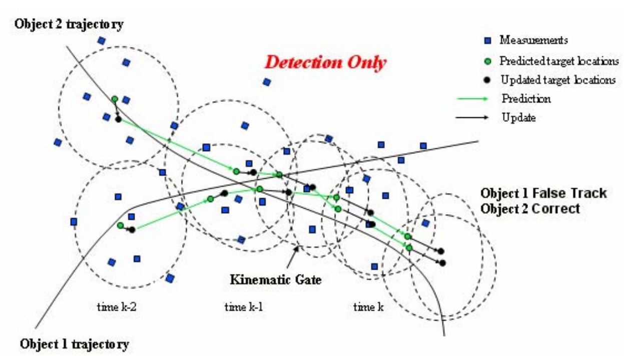


Figure 2. Data Association Problem with only Position Measurements.

As we can see on the far left of Figure 2, a kinematic gate can isolate position measurements that are near the predicted measurement for each object's track. In the case that one of the true measurements falls within the kinematic gate of the predicted position, that measurement would be designated as the true position measurement. The position measurement of object 2 would be assigned to object 1's track if position measurements from another object fell within the predicted kinematic gate of the object track as shown in the middle of Figure 2, which would be an incorrect assignment. Once the tracker locks on to another object, or uses the position hits of the other object's clutter, the tracker assumes that the hits of the second object are true hits for the first object as shown on the far right of Figure 2.

One way to correct for this measurement-to-target assignment mistake is to leverage other information, such as the target identity to help resolve which position measurements are assigned to specific object tracks. For example, we could use a high resolution EO/IR sensor to ID a moving target and use the false and true EO/IR scans as positional information [10]. To illustrate how the ID information may help in data association, Figure 3 illustrates the process of how a target-ID can refine the positional measurement to select the validated measurement from the cluttered measurements.

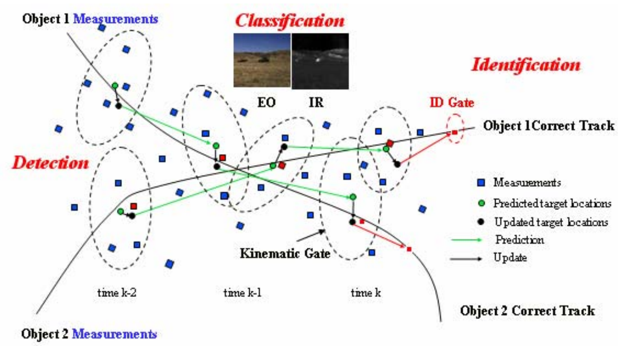


Figure 3. Data Association using ID and Position Measurements.

A few *tracking and ID algorithms* have been proposed [10, 11, 16, 17]. These approaches use target track information to cue target recognition and detection. We seek to expand on this idea by allowing for a multiresolution capability to track targets in a wide-area search mode and ID relevant targets in precision tracking. Identification goes beyond recognition by assigning a single target ID to each target. In this paper, we are interested in controlling the sensor resolution to aid the track and ID process with a series of sensors.

This paper develops a multiresolution EO/IR track and identification data association (MEIDA) technique to distinguish between multiple moving targets in clutter. Section 2 overviews the EO/IR target identification fusion based on the data sets. Section 3 discusses track and ID data association. Section 4 describes the problem formulation and Section 5 details the mathematics of the algorithm. Section 6 presents results and Section 7 draws conclusions.

2 EO/IR Target Recognition & Fusion

In the case of day/night analysis, many surveillance systems incorporate both electro-optical and infrared (IR) camera systems to be able to capture the visible spectrum in the day and thermal imaging at night. EO/IR images are subject to the camera-to-target range.[18] In search mode, it would be desirable to stay far way to find targets (track initiation). As targets are acquired, the tracker operates in a track maintenance mode to follow targets; however, to identify the targets when they are closely spaced, the sensor manager must change the resolution. While each sensor is better for a given lighting condition, the sensor suite simultaneously outputs both images (see **Figure 1**), for a given resolution.

Synthetic target images were generated for 360 degrees for 4 targets at three resolutions (high, medium, and low). The highest resolution data was generated to yield 200 times more pixels on target than the lowest resolution, and the medium resolution had 10 times more pixels on target than the lowest resolution. Each image can facilitate target ID. A set of training images and a set of test images were created for target ID. The ID consisted of determining the associated confusion matrix for the set of targets at each resolution for each of the 360 degrees. The resolution is a function of the range and the corresponding number of pixels on target is shown in **Figure 4**. The gaps in the data are due to a percentage of random samples being removed from the test data to decrease simulation run times. Obviously, target recognition improves with more pixels on target. Although greater sensor resolution is the biggest contributing factor, vehicles orientation also contributes to the number of pixels on targets as can be scene in **Figure 4** at broadside and head and tail on perspectives. Thus, the target recognition would be better with higher resolution, but is still subject to the orientation and size of the target.

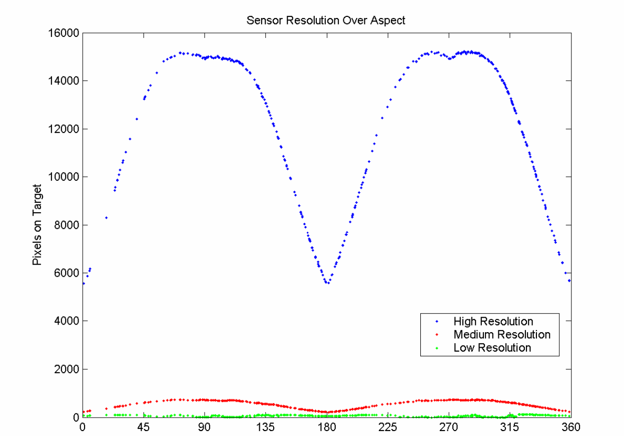


Figure 4. Pixels on target.

The target recognition is better at the high resolution versus the low resolution, as shown in **Figure 5**. From Figure 5, we see that at the high resolution, the target ID is of higher fidelity than that of the low resolution. Since the EO/IR images were synthetically generated, the ID results were a function of operating conditions (i.e. we have better ID performance with fewer operating conditions of atmospheric, lighting, etc). The belief values were calculated using a Bayesian likelihood based on peak signal returns and target shape features. Likewise, the fused EO/IR results of Figure 5 are a function of selecting the optimum match of either the EO or the IR image (which we will use in the simulation – Section 6). Finally, a discrete selection of the target was made from a set of 4 targets with one member of the set being an unknown quantity. In many cases for the low resolution, the target selection was unknown (many points at the origin of the polar plot). In this case of low belief, the tracker just uses the kinematic measurement, with no selection of the target ID to weight the measurements.

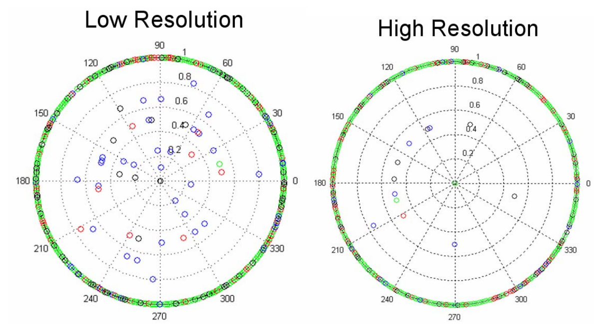


Figure 5. Target ID at low and high resolutions. (Different colors represent different target Pr(ID) for various aspects versus the target set).

3 Track and ID Fusion

The ability to perform track and ID fusion requires sensor-processed classifications from different levels. These levels could be generic(car), feature(wheeled), type(sedan) or specific(license plate). Like multitarget data association algorithms for accurately tracking targets in the presence of clutter, we assume that detected targets can be tracked from a sequence of center-of-gravity and pose positional data. However, for a given sensor/target scenario, we assume detected classifications can effectively discern target ID. ID information can be achieved either through experience of target movement, training, or predicted. For example, identifying a target requires the correct orientation and speed estimate. Two targets of the same type may be crossing in space, but since they can not occupy the same location, they would each have a different orientation relative to a sensor. By exploiting the orientation, velocity, and multiresolution EO/IR feature information, each target can be assessed for the correct track-ID association.

The capability of a sensor to track and ID targets simultaneously includes finding the target center for tracking, determining the target pose, and searching the neighboring characteristics for discerning salient features for association to a specific target type. By partitioning kinematic and ID sensor data, associations at different levels can be used for either coarse(track) or fine (ID) target analysis. For example, features [10] can be used to get an ID with uncertainty; however if many features are fused, the identity improves and helps eliminate clutter.

The tracker must use the available features to discern an object (*identify* a target) which is a subset of Automatic Target Recognition (ATR). Certain features are inherently more useful in recognizing a target than others. For instance, identifying a large car versus a small car would result from an analysis of the length-to-width ratio. However, obtaining these features is a function of sensor resolution. Additionally, decoupling information can be used for a single-platform observer to fuse information from a sequence of sensor data or for a multiple-platform scenario [9] in which fusing is performed from different geometrical positions. Further information on the development of the belief-ID derivation is found in [10].

The problem of track level and ID-level fusion has characteristic *tradeoffs* about which the tracker must decide. For close targets, it is useful to keep an accurate track on multiple targets. The intelligent processor performs target-to-ID association at multiple levels and can either track targets at a low resolution or ID targets at a higher resolution. By leveraging knowledge about target types, fusion algorithms can significantly reduce processing time for tracking and identifying targets. For separated targets, resources may exist to identify each target. Hence, due to a limited set of resources and/or processor time, a trade-off exists between the identification and tracking of a target.

4 Problem Formulation

Consider an environment in which a tracker is monitoring multiple moving targets with stationary clutter. By assumption, the tracking sensor is able to detect target signatures. Assume that the 2-D region is composed of T targets with f features. Dynamic target measurements z are taken at time steps k, which include target kinematic and identification features $\mathbf{z}(\mathrm{k}) = [x_t(\mathrm{k}), \mathrm{f}_1, \ldots \mathrm{f}_n]$.

Any sensor can measure independently of the others, and the outcome of each measurement may contain kinematic or feature variables indicating any target. The features for each sensor are similar, but need to be extracted and applied to the separate targets for classification. The probability density of each measurement depends on whether the target is actually present or not. Further assume that a fixed number of kinematic and feature measurements will be taken at each time interval, where we model the clutter composing spurious measurements. A final decision from the MEIDA algorithm is rendered as to which $[x, y]$ measurement is associated with the target-type.

The *multisensor-multitarget tracking and identification problem* is to determine which measured kinematic features should be associated with which ID features in order to optimize the probability that targets are tracked and identified correctly after z measurements. The multilevel feature fusion problem is formulated and solved by using concepts developed using the belief filter [10]. For the symmetric-target case, the "association rule" uses the measurement with the highest target probability.

5 Track and ID Data Association

5.1 Tracking Belief Filter

The target *state* and *true measurement* are assumed to evolve in time according to:

$$\mathbf{x}(k+1) = \mathbf{F}(k)\,\mathbf{x}(k) + \mathbf{v}(k) \quad (1)$$

$$\mathbf{z}(k) = \mathbf{H}(k)\,\mathbf{x}(k) + \mathbf{w}(k) \quad (2)$$

where $\mathbf{v}(k)$ and $\mathbf{w}(k)$ are zero-mean mutually independent white Gaussian noise sequences with known covariance matrices $\mathbf{Q}(k)$ and $\mathbf{R}(k)$, respectively. We assume each target has a separate track and set up multiple state equations. *Spurious measurements* are uniformly distributed in the measurement space. Tracks are assumed initialized at an initial state estimate $\mathbf{x}(0)$, contain a known number of targets determined from the scenario, and have associated covariances [1].

The *tracking ID filter* devotes equal attention to every validated kinematic or ID measurement and cycles through measurements until a believable set of object IDs is refined to associate one object per track. For an initial set of measurements, a hypothesized number of tracks and objects of interest is assumed to comprise the entire set. Objects are possible position measurements without ID confirmation. Successive measurements and updates from the combined feature and track measurements determine the set of plausible targets. The measurement filter assumes the *past* is summarized by an *approximate sufficient statistic* – track state and ID state estimates (approximate conditional mean) and covariances for each object.

The belief measurement information $\mathbf{Bel}_{\mathrm{k}}^{t} = \mathbf{M} \bullet \mathbf{Bel}_{\mathrm{k-1}}^{t}$, derived from the classification measurements of the target image, represents the belief update states of the ID measurements. The $\mathbf{M}$ matrix is the Markov transition matrix, which represents the similarity of objects. The similarity of objects represents how the belief in an object type may be related to other objects of the same or different type.

The *measurement-to-track association probabilities* are *computed across* the objects and these probabilities are computed only for the *latest set of measurements*. The conditional probabilities of the joint track-ID association events pertaining to the current time k are defined as $\boldsymbol{\theta}_{jot_{\mathrm{k}}}$, where $\boldsymbol{\theta}_{jot_{\mathrm{k}}}$ is the event that object center-of-gravity measurement j originated from object o and track t, $j = 1, \ldots, m_{\mathrm{k}}$; $o = 0, 1, \ldots, \mathrm{O_n}$, where m_{k} is the total number of measurements for each time step and $\mathrm{O_n}$ is the unknown number of objects. Note, for purposes of tracking and ID, we define $i = 1, \ldots, m_{\mathrm{k}}$ for the entire measurement set while $j = 1, \ldots, m_{\mathrm{k}}$ is for tracking and $o = 1 \ldots, m_{\mathrm{k}}$ is for object ID.

A validation gate for each object bounds the believable joint measurement events, but not in the evaluation of their probabilities. The *plausible validation matrix*: $\mathbf{\Omega} = |\,\boldsymbol{\omega}_{jt}\,|$ is generated for *each* object of a given track which comprises binary elements that indicate if measurement j lies in the validation gate of track t. The index $t = 0$ represents "the empty set of tracks" and the corresponding column of $\boldsymbol{\Omega}$ includes all measurements, since each measurement could have originated from clutter, false alarm, or true object [1].

For a track event, we have:

$$|\,\hat{\omega}_{jt}(\theta)| \triangleq \begin{cases} 1 & \text{if } \boldsymbol{\theta}^{i}_{jt} \in \theta;\ [\mathbf{z}]^{i}_{k} \subset t \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where measurement $[\mathbf{z}]^{i}_{k}$ originated from track t

For an ID-belief event, which is above a predetermined ID threshold,

$$|\,\hat{\omega}_{oO}(\theta)| \triangleq \begin{cases} 1 & \text{if } \theta^{i}_{oO} \in \theta;\ [\mathbf{Bel}]^{i}_{O_k} \Leftrightarrow o \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where measurement $[\mathbf{Bel}]^{i}_{O_k}$ is associated ($\Leftrightarrow$) with object o.

Since MEIDA is tracking multiple objects, o, assuming one for each track, t, MEIDA has to determine the ID-belief in each object from a known database comparison. While these IDs are processed over time to discern the object, for each measurement, MEIDA must determine if the track-ID measurements are plausible. MEIDA uses the current ID-beliefs to update the association matrix. If the belief in the object is above a threshold, MEIDA declares the measurement i, to be plausible for the target. Note, for plausibility, the threshold is lower than an ID declaration.

5.2 Data Association

Since we have assessed the continuous-kinematic information and the discrete-classification event, we can now assess the intersection of kinematic and ID information for simultaneous object tracking and ID. Note, ID goes beyond object detection, recognition, and classification, where we define ID as the classification of an object-type for a given track to associate an object classification to a track. For instance, two objects of the same class still need to be associated with a specific track. We need to address feasible events for either a validated kinematic measurement or a validated ID. A kinematic-ID *joint association event* consists of the values in $\boldsymbol{\Omega}$ corresponding to the associations in θ_{jot},

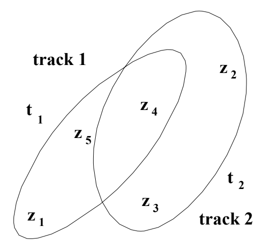
$$|\,\hat{\omega}_{jot}(\theta)| \triangleq \begin{cases} 1 & \text{if } \theta^{i}_{jot} \in \theta\,^{*} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where (*) measurement $[\mathbf{z}]^{i}_{k}$ originated from track t *with* a $[\mathbf{Bel}]^{i}_{O_k}$ for a given O_{ot} and

$$\hat{\omega}_{jot}(\theta) = \hat{\omega}_{jt}(\theta) \oplus \hat{\omega}_{oO}(\theta). \tag{6}$$

Note, we define the indices as *jot* since O is the number of objects which is equal to the number of tracks.

These joint events will be assessed with "β" weights [1] to determine the extent of belief in the associations. To process the believability of track associations, augmented with the ID information, we set up a matrix formulation. For example, we have a set of kinematic measurements $\mathbf{z}_i$ with a $\mathbf{Bel}_o$ and put them into the event association matrix as illustrated in **Figure 6**. The upper left of a box represents the track information where a "1" indicates the kinematic measurement lies within a gated position measurement. The lower right represents the belief in an object type of any class except the unknown class where a believable object receives a "1". Columns are for tracks and rows for measurements. These generalized equations propagate ID-filtered, predicted ID measurements in time.



	T_1 / Bel_1	T_2 / Bel_2
z_1 / Bel_{z_1}	1 (1) 1	1 (0) 0	0 (0) 1
z_2 / Bel_{z_2}	1 (1) 1	0 (0) 0	1 (0) 0
z_3 / Bel_{z_3}	1 (1) 1	0 (0) 0	1 (1) 1
z_4 / Bel_{z_4}	1 (1) 1	1 (0) 0	1 (0) 0
z_5 / Bel_{z_5}	1 (1) 1	1 (1) 1	0 (0) 0

Figure 6. Tracking and Classification Joint Association

MEIDA processes event matrices with an "AND" function in the case of joint association allowing for plausible events from either the track or classification. [Note, the "OR" function could be used for high clutter, but was not used.] To determine the event plausibility, MEIDA uses the validation region for track measurements and uses a threshold, or *classification gate*, to determine a target-type ID match associated with a given track. **Figure 7** illustrates the "AND" function. Note, MEIDA rejects non-believable measurements and measurements that lie outside the kinematic validation gate.

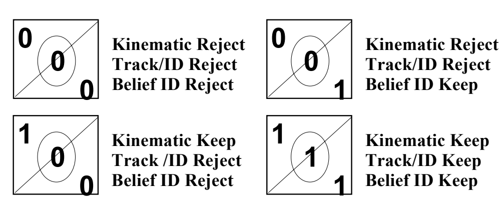


Figure 7. Believable Events for the association matrix.

MEIDA sets up the state and probability values for the determination of the weights assigned to these associations. A *track-ID association event* has [1]

i) a single object-type measurement from a source:

$$\sum_{o=0}^{O_n} \hat{\omega}_{jot}(\theta^i_{jot}) = 1 \quad \forall j \tag{7}$$

ii) and at most one object-type measurement ID originating from a object for a given track:

$$\delta_t(\theta) \stackrel{\Delta}{=} \sum_{j=1}^{m_k} \hat{\omega}_{jot}(\theta^i_{jot}) \leq 1 \tag{8}$$

The event matrices, $\hat{\Omega}$ for each track, corresponding to ID events can be done by scanning $\boldsymbol{\Omega}$ and picking one unit/row and one unit/column for the estimated set of tracks except for t = 0. In the case that MEIDA has generated event matrices for an estimated number of tracks with different object types, MEIDA needs to assess the combination of feature measurements to infer the correct number of tracked objects that comprise the set. The binary variable $\delta_t(\theta_{jot_k})$ is called the *track detection indicator* [1] since it indicates whether a measurement is associated with the object o and track t in event θ_{jot_k}, i.e. whether it has been detected.

The *measurement association indicator*

$$\tau_j(\theta_{jot_k}) \stackrel{\Delta}{=} \sum_{j=1}^{m_k} \hat{\omega}_{jot}(\theta_{jot_k}) \tag{9}$$

indicates measurement j is associated with the track t in event θ_{jot_k}.

The number of *false measurements* in event θ is

$$\phi(\theta) = \sum_{j-1}^{m} [\, 1 - \tau_j(\theta)\,] \tag{10}$$

The *joint association event probabilities* are, using Bayes' Formula:

$$\begin{aligned} P\{\theta(k)|\mathbf{Z}^k\} &= P\{\theta(k)|\mathbf{Z}(k),\mathrm{m}(k),\mathbf{Z}^{k-1}\} \\ &= \frac{1}{c}\, p[\mathbf{Z}(k) \mid \theta(k),\mathrm{m}(k),\mathbf{Z}^{k-1}]\, P\{\theta(k) \mid \mathrm{m}(k)\} \\ &= \frac{1}{c} \prod_{j=1}^{m(k)-\phi(k)} V\, \{f_{t_t}(k)\, [\mathbf{z}_j(k)]\}^{\tau_j} \end{aligned} \tag{11}$$

where c is the normalization constant.

The number of *measurement-to-target assignment events* $\theta(k)$ is the number of targets to which a measurement is assigned under the same detection event $[\mathrm{m}(k) - \phi]$. The *target indicators* $\delta_t(\theta)$ are used to select the probabilities of detecting and not detecting events under consideration.

5.3 Fused Track and ID State Estimation

Assuming the targets conditioned on the past observations are *mutually independent*, the decoupled state estimation uses the *marginal association probabilities*, which are found from the joint probabilities by summing all the joint events in which the marginal track and classification events result. The beta weights [1] are:

$$\begin{aligned} \beta^t_{jo_k} &\stackrel{\Delta}{=} P\{\theta_{jot_k} \mid \mathbf{Z}^k\} \\ &= \sum_{\theta} P\{\theta_{jot_k} \mid \mathbf{Z}^k\}\hat{\omega}_{jo}(\theta_{jot_k}) \end{aligned} \tag{12}$$

MEIDA decomposes the object-state estimation with respect to the *location* of each object of the *latest set* of validated belief-set and kinematic-set measurements. The measurements have been used to get the classification beliefs in the object types, to set up a simultaneous tracking and ID recursion for each object in the set, where ID is the classification of each object for a given track of data. For each object measurement, we use the total probability theorem to get the *conditional mean* of the state at time k can be written as:

$$\hat{\mathbf{X}}^t_{k|k} = \sum_{i=0}^{m^o_k} \hat{\mathbf{X}}^{ti}_{k|k}\, \beta^{ti}_k\,, \tag{13}$$

where $\hat{\mathbf{X}}^t_{k|k}$ is the updated state conditioned on the event that the i^{th} validated object measurement is correct for track t. The covariance propagation is:

$$\mathbf{P}^t_{k|k-1} = \mathbf{F}^t_{k-1}\, \mathbf{P}^t_{k-1}\, (\mathbf{F}^t_{k-1})^T + \bar{\mathbf{Q}}^t_{k-1}, \text{ where } \bar{\mathbf{Q}}_k = \begin{bmatrix} \mathbf{Q}_k & 0 \\ 0 & \mathbf{B}_k \end{bmatrix}$$

for each track t.

We can obtain the innovation covariance $\mathbf{S}_k$ with the associated $\mathbf{R}_k$ and measured $\mathbf{D}_k$ by:

$$\mathbf{S}^t_k = \mathbf{H}^{o_t}_k\, \mathbf{P}^t_{k|k-1}\, (\mathbf{H}^{o_t}_k)^T + \bar{\mathbf{R}}^t_k, \text{ where } \bar{\mathbf{R}}_k = \begin{bmatrix} \mathbf{R}_k & 0 \\ 0 & \mathbf{D}_k \end{bmatrix}$$

Since $\mathbf{S}_k$ is the innovation covariance update, we can use $\mathbf{S}_k$ to gate measurements based on the uncertainty with the associated track and IDs.

Validation: At k, two measurements are available for object o for a given track t: $\mathbf{z}^T_{k-1}$, and $\mathbf{z}^T_k$, from which position, velocity, pose, and ID features can be extracted form the belief track vectors. Validation, based on track and ID information, is performed to determine which track-belief measurements fall into the kinematic region of interest. Validation can be described as

$$(z^t_k - \hat{z}^{lt}_{k|k-1})^T\, [\mathbf{S}^t_k]^{-1}\, (z^t_k - \hat{z}^{lt}_{k|k-1}) \leq \gamma \quad \text{for } l = 1 \ldots m^o_k \tag{14}$$

where γ is a validation threshold obtained from a χ^2 table for a degree of freedom of 14 (4 for kinematic states and 10 for target beliefs) and $\mathbf{S}_k$ stands for the largest among the predicted track belief covariance**,** i.e., $\det(\mathbf{S}_k) \geq \det(\mathbf{S}^t_k)$ for $t = 1,2,\ldots,n$ where n is the number of states. The combined predicted track belief, $\hat{z}_{k|k-1}$, is given by $E\{\mathbf{z}_k|\{\beta\}^s_{o=1}, \mathbf{Z}^{k-1}\}$ where s is the set of object beliefs for a track.

Data association for β_l^{ti} : Data association performed for each belief object-track is similar to that in PDA and the details can be found in [1]. The association probabilities for l validated object measurements are:

$$\beta_l^{\,t} = \frac{e_l^{\,t}}{b + \sum_{l=1}^{m_k^o} e_l^{\,t}},\ l = 1, 2, \ldots, m_k^o \tag{15}$$

$$\beta_0^{\,t} = \frac{b}{b + \sum_{l=1}^{m_k^o} e_l^{\,t}}, \tag{16}$$

$$\text{where } e_l^{\,t} = P_G^{-1}\, N(\underline{0}, \mathbf{S}_k^t) \tag{17}$$

$$b = m_k^o\,(1 - P_D P_G)\,[P_D P_G V_k]^{-1} \tag{18}$$

with m_k^o defining the number of validated object measurements, P_G assessing the probability that augmented belief track measurements fall into the *validation region,* and P_D representing a detection probability. For the MEIDA case, we vary the innovation covariance ($\mathbf{S}_k$), P_D, P_G proportionally to the sensor manager collection resolution (i.e. higher resolution $\rightarrow$ higher P_D, higher P_G, & lower $\mathbf{S}_k$). The lower $\mathbf{S}_k$ for the higher resolution is a result of changing the prediction, which results after a few track instances. The *volume of the validation gate* is

$$V_k = \mathbf{C}_d\, \gamma^{d/2}\, |\mathbf{S}_k|^{1/2}, \tag{19}$$

where $\mathbf{C}_d$ is the unit hypersphere volume of dimension d, the dimension of the augmented belief-track measurement.

Kinematic belief-probabilistic update: The object belief-probabilistic track update is performed as a full rate system to combine the state, innovation, and covariances.

$$\hat{\mathbf{X}}_{k|k}^{t} = \hat{\mathbf{X}}_{k-1|k-1}^{t} + \mathbf{W}_k^{\,t} \sum_{l=1}^{m_k^o} \beta_{lk}^{t}\, \mathbf{v}_{lk}^{t} \tag{20}$$

and

$$\mathbf{P}_{k|k}^{t} = \beta_0^{\,t}\, \mathbf{P}_{k|k-1}^{t} + (1 - \beta_0^{\,t})\, \mathbf{P}_{k|k}^{*} +$$

$$\mathbf{W}_k^{\,t} \left[\sum_{l=1}^{m_k^o} \beta_{lk}^{t}\, \mathbf{v}_{lk}^{t}\, [\mathbf{v}_{lk}^{t}]^T - \mathbf{v}_k^t [\mathbf{v}_k^t]^T \right] (\mathbf{W}_k^t)^T \tag{21}$$

where

$$\mathbf{P}_{k|k}^{*} = \left[\, \mathrm{I} - \mathbf{W}_k^{\,t}\, \mathbf{H}_k^{o_t} \right] \mathbf{P}_{k|k-1}^{t} \text{ and } \mathbf{v}_k = \sum_{l=1}^{m_k^o} \beta_{lk}^{\,t}\, \mathbf{v}_{lk}^{t} \tag{22}$$

$$\mathbf{W}_k^t = \mathbf{P}_{k|k-1}^t\, [\mathbf{H}_k^{o_t}]^T\, (\mathbf{S}_k^t)^{-1} \tag{23}$$

where $\mathbf{H}_k^{o_t}$ is the measurement matrix that is calculated for each object pose, ϕ, and estimated position of track t.

6 Initial Results

The MEIDA track and ID method is evaluated with a Monte Carlo simulation and the performance metric is position state error (i.e. RMS). The ID information is a result of the fused EO/IR discrete result where the aggregated comparison between true image versus corresponding images over a 20 degree window for the various targets. The probability results from the normalized number of discrete selections over the comparisons (t targets, d degrees). The high resolution case results in better probabilities than the low resolution case. As detailed in the Figure 8 below, by the true trajectory; the targets 1) start with position and velocity, 2) pass by each other at a close distance, and 3) finish with a specified direction. There was added noise to the true target position and clutter comprised of 5 spurious measurements around a target. Even with closely spaced targets, the MEIDA tracker was able to locate, track, and identify the targets with clutter.

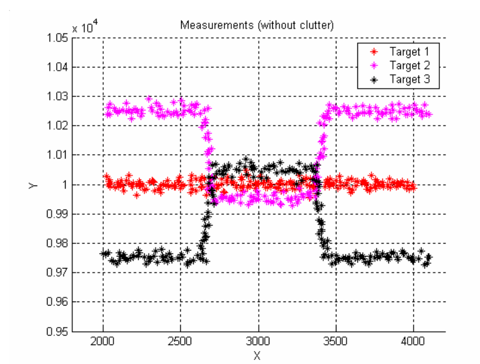


Figure 8. Tracking scenario with noise.

Figure 9 shows the JPDAF effectiveness when targets are separated by a large distance. The separation allows for the determination of a validation gate size that associates the correct measurements to tracks. However, as targets are close, the tracker combines all the targets into one track, due to the clutter.

Figure 9. Tracking without ID information.

Figure 10 shows the same case as Figure 9 with identification information that helps the tracker better associate the true position measurements from clutter.

Target beliefs increased throughout the run as the target was repeatedly identified as the same target.

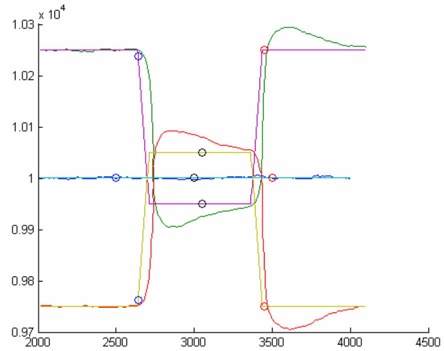


Figure 10. Tracking with ID information.

Note, as the covariance grows in target position estimate, the sensor manager switches from a low-resolution mode to a high-resolution mode to better discern the target types. As targets separate, the covariance decreases and the sensor manager switches back to the low-resolution mode (show in **Figure 11**).

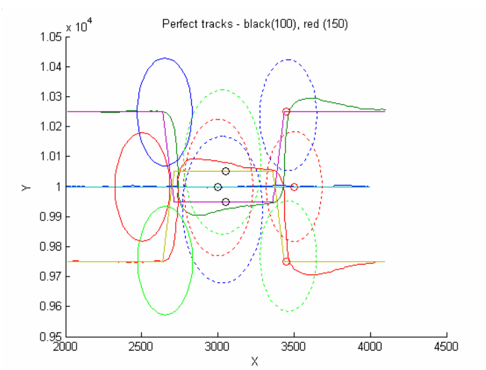


Figure 11. Tracking with ID covariance information.

7 Discussion & Conclusions

Conventional measurement tracking techniques have difficulty with data association when position measurements are close. The MEIDA algorithm, which uses the identification information from an EO/IR sensor suite, helps to associate the correct measurement to the correct targets. In the presence of clutter, the novel algorithm utilizes parsimony for processing by incorporation of covariance information to select sensor resolution. The MEIDA can be utilized in a time-constrained weak-sensor scenario to get a general target location and a positive ID (cued high resolution) that can be used to augment a data association tracker.

In a series of simulation experiments, the MEIDA performed well resulting in a desirable solution for closely spaced moving targets, and at a faster rate than conventional tracking methodologies. The faster rate resulted from a reduction in the gate size to eliminate clutter. The presented technique demonstrates promise for multitarget tracking problems and warrants further exploration in problems where environmental effects, occlusions, lost sensor data, and unknown targets require a sensor manager to control sensor resolution to optimize tracking performance. Future work will explore the sensitivity of the results to a higher fidelity EO/IR target recognition algorithm over more operating conditions and utilize methods that afford track initiation (i.e. IPDA [8]).

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