Presented at Conference on Decision and Control, Tampa, FL, 1998, pg. 239-244.

Simultaneous Feature-Based Identification and Track Fusion

Erik Blasch
AFRL/SNAT
2241 Avionics Cir.
WPAFB, OH 45433
blaschep@sensors.wpafb.af.mil

Lang Hong
Dept. of Electrical Engineering
Wright State University
Dayton, OH 45435
lhong@cs.wright.edu

Abstract

A tactical pilot typically experiences difficulty in maintaining accurate identification on multiple-interacting targets in the presence of clutter. We propose a multilevel feature-based association (MFBA) algorithm to aid a pilot in a dynamic multi-target environment. We investigate MFBA for an air-to-ground scenario in which a plane, equipped with a high-range resolution radar sensor processes kinematic and target features at different levels, and fuses these features to simultaneously track and identify targets.

1. Introduction

The problem of multitarget tracking and identification (ID) is a subset of sensor management, which includes selecting sensors, sensor recognition policies, and tracking algorithms for a given set of mission requirements [1]. For example, in a typical tactical aircraft, the onboard sensors are an active radar, an electro-optical sensor, and a passive radar sensing device, with each sensor having a variety of modes in which it can operate and features it can detect. These sensors make kinematic and ID measurements to detect, track, and classify objects of interest while reducing pilot workload. The ultimate objective of the sensor management system involves pilot survival and mission success. In a dynamic and uncertain environment, the onboard sensor manager must select the correct sensor to ID the correct target at a given time. Thus, the sensor manager must control the measurement sequencing process for effective tracking as well as discern threatening targets. Techniques such as reinforcement and association learning have been applied for searching, detection, and identification [2].

Multitarget tracking in the presence of clutter has been investigated through the use of data association algorithms [3]. Likewise, other multisensor multiplatform fusion algorithms focus on identifying targets from multiple look sequences of sensor data [4]. The merging of these algorithms can be accomplished by investigating the similar features between the algorithms. Track fusion uses kinematic features and ID fusion uses target-type features. By utilizing the merits of data association in multilevel feature fusion, we seek to simultaneously track and identify targets.

A few *tracking and identification algorithms* have been proposed [5,6,7]. These approaches, although influential in this work, rely on the Bayes' rule for identification. A limitation of using a Bayesian analysis is that it does not capture incomplete knowledge. For instance, there are times when unknown targets might be of interest that are not known at algorithm initiation. At other times, there are unknown number of targets to track. Layne [8] utilizes an automatic target recognition (ATR) and tracking filter in a multiple model estimator (MME) approach; we seek to expand on this idea by allowing for the capability to discern unknown relevant targets. Additionally, by incorporating a general theory for features, any combination of sensors and targets can be captured, such as in biological, manufacturing, and economic scenarios.

This paper develops a multilevel feature-based association (MFBA) for simultaneously tracking and identifying targets. The MFBA algorithm leverages the *multiple-pattern data association* tracking algorithm [4]. MFBA may offer a means to control some aspects of the computational burdens experienced by analytical optimization techniques while providing an effective solution for multitarget tracking and ID in the presence of clutter. Section 2 overviews feature track and ID level fusion. Section 3 describes the problem formulation and Section 4 details mathematics of the algorithm. Section 5 presents results and Section 6 draws some conclusions.

2. Intelligent Feature and Track Level Fusion

The ability to perform track and ID fusion requires sensor-processed features from different levels. 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 high range resolution (HRR) signature features can effectively discern target types. Feature-to-target mappings can be achieved either through another observer's experience, association learning, or predicted. By leveraging knowledge about target types, fusion algorithms can significantly reduce processing time for tracking and identifying targets. In addition, correlating kinematic features with signatures will allow for identifying targets at the same time tracking is performed. MFBA applies to multisensor applications for either similar-type multiple-platform or single-platform different-type sensors, as

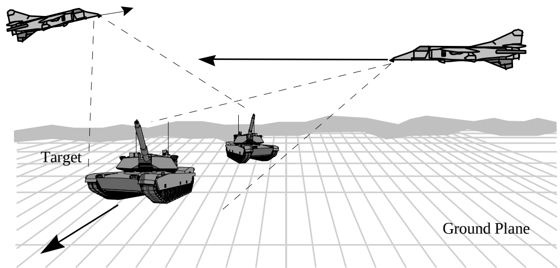

Figure 1. Multifeature-Multitarget Tracking and Target identification.

shown in Figure 1. Thus, integration of information can take place at either the feature or track level fusion.

Intelligence in tracking is the ability of an agent to discern salient features from a sensor image. Since information available to an observer is restricted to the sensed image, it constrains the possible information for tracking and identification. The intelligent approach would utilize each sensor for a given perceived outcome. The ability of the observer to track and ID targets simultaneously includes finding the target center for tracking, determining the target pose, and searching the neighboring features for discerning salient features to associate the features to a specific class of targets. By partitioning kinematic and ID sensor data, feature association at different levels can be used for either coarse(track) or fine(ID) target analysis. 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 in which fusing is performed from different geometrical positions.

The problem of track level and feature-level fusion has characteristic *tradeoffs* about which the intelligent agent must decide. Situational awareness includes both the identification and locality detection of competitors and allies. For close targets, it is useful to keep an accurate track for any target that threatens survival. Figure 1 shows the case in which the forward tank has an articulation that threatens the plane flying overhead, but not the survival of the second plane. For this situation, the overflying plane would want to perform ID, while the other platform would perform tracking. Together, the multiplatform scenario would insure the survival of both planes. Hence, due to a limited set of resources and/or processor time, a trade-off exists between the two types of fusion. The intelligent processor performs feature-association at multiple levels and can either track targets at a low resolution or ID targets at a higher resolution.

3.0 Problem Formulation

Consider Figure 1 as an environment that the two pilots are monitoring. Each pilot with his available platform would want either to track or ID targets depending on the situation. *Identifying* a target is a subset of ATR algorithms in which the observer must use the available features to discern the object. Certain features are inherently more useful in recognizing a target than others. For instance, identifying a large plane versus a small plane would result from an analysis of the wing to length ratio. In this scenario, we use a conventional platform HRR sensor which has multiresolution distance-independent all-weather capability for the MFBA algorithm. Additionally, HRR can perform either in spotlight or stripmap modes for multiple platform scenarios as shown in Figure 2.

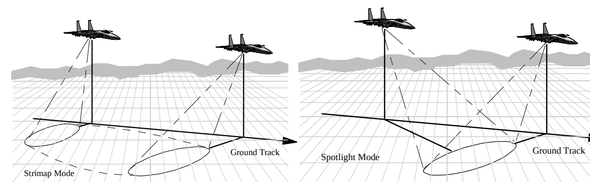

Figure 2. HRR Mode Multiplatform Tradeoff.

By assumption, the aircraft carries a HRR sensor able to detect target signatures. Assume that the region in Figure 2, the 2-D frame, is composed of T targets with f features. For the HRR profile, Figure 3, the features are the peak measurements and the distance, d, between the peak features. Dynamic target measurements z are taken at time steps k, which include target kinematics and identification features $z(k) = [x_t(k), f_1, \ldots f_n]$.

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. 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 form the MFBA algorithm is rendered as to which [x, y] measurement is associated with the target-type. The feature-to-target mapping is determined *a priori* from the

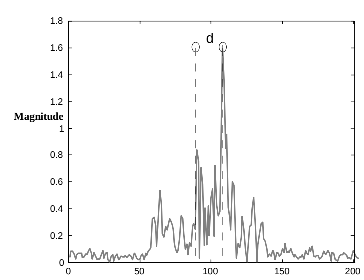

Figure 3. HRR Plot.

learned feature recognition of HRR signature and unknown targets are tracked but not identified.

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 from probability data association. For the symmetric-target case, the "association rule" associates the measurement with the highest target probability. Since unknown targets are possible, a sub-optimal result occurs when making the final decision about asymmetric target types from the different perspectives of the observer.

Two feature level fusion methods are implemented. The first, which we call *Measurement Tracking*, searches through all the measurements and probabilistically chooses the measurement most likely to be associated with the target. The second method, *Feature Identification*, is a procedure that uses feature measurements for believable target IDs to discriminate between targets. By combining these algorithms in the MFBA, targets close together can be effectively identified and tracked.

4.0 Feature Tracking and Identification

4.1 Tracking Belief Filter (TBF)

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

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

$$z(k) = H(k)x(k) + w(k) \tag{2}$$

where $v(k)$ and $w(k)$ are zero-mean mutually independent white Gaussian noise sequences with known covariance matrices $Q(k)$ and $R(k)$, respectively. *Spurious measurements* are uniformly distributed in the measurement space. Tracks are assumed initialized at an initial state estimate $x(0)$, contain a known number of targets determined from the scenario, and have associated covariances.

The *measurement-to-target association probabilities* are computed across the targets and these probabilities are computed only for the *latest set of measurements*. The conditional probabilities of the joint-target association events pertaining to the current time *k* is defined as $\theta(k)$, where θ_{jt} is the event that measurement *j* originated from target *t*, $j = 1,\ldots, m(k)$; $t = 0, 1,\ldots, N_t$, where $m(k)$ is the total number of measurements for each time step, *k* is the time of measurements, and N_t is the known number of targets. A *validation gate* is used for the selection of the believable joint events, but not in the evaluation of their probabilities.

The *Plausible validation matrix* $\Omega = |\,\omega_{jt}\,|$ is composed of binary elements that indicate if measurement *j* lies in the validation gate of target *t*. The index $t = 0$ stands for "none of the targets" and the corresponding column of Ω includes all measurements, since each measurement could have originated from clutter, false alarm, or the true target, or an unknown target.

A *joint association event* consists of the values in Ω corresponding to the associations in θ,

$$\hat{\Omega}(\theta) = |\,\hat{\omega}_{jt}(\theta)| = \begin{cases} 1 & \text{if } \theta_{jt} \in \theta \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

A *believable association event* has

i) A single measurement source:

$$\sum_{t=0}^{N_T} \hat{\omega}_{jt}(\theta) = 1 \quad \forall\, j \tag{4}$$

ii) At most one measurement originating from a target:

$$\delta_t(\theta) \triangleq \sum_{j=1}^{m} \hat{\omega}_{jt}(\theta) \le 1 \tag{5}$$

The generation of event matrices, $\hat{\Omega}$, corresponding to believable events can be done by scanning Ω and picking one unit/ row and one unit/column except for $t = 0$.

The binary variable $\delta_t(\theta)$ is called the *target detection indicator* since it indicates whether a measurement is associated with the target *t* in event θ, i.e., whether it has been detected.

The *measurement association indicator*

$$\tau_j(\theta) \triangleq \sum_{t=1}^{m} \hat{\omega}_{jt}(\theta) \tag{6}$$

indicates measurement *j* is associated with the target *t* in event θ.

The number of *false measurements* in event θ is

$$\phi(\theta) = \sum_{j-1}^{m} [\,1 - \tau_j(\theta)\,] \tag{7}$$

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

$$\begin{aligned} P\{\theta(k)|Z^k\} &= P\{\theta(k)|Z(k),m(k),Z^{k-1}\} \\ &= \frac{1}{c}\, p[Z(k)\mid \theta(k),m(k),Z^{k-1}]\; P\{\theta(k)\mid m(k)\} \\ &= \frac{1}{c} \prod_{j=1}^{m(k)-\phi(k)} V\,\{f_{t_t}(k)\,[z_j(k)]\}^{\tau_j} \end{aligned} \tag{8}$$

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 $[m(k) - \phi]$. The *target indicators* $\delta_t(\theta)$ are used to select the probabilities of detecting and not detecting events under consideration.

A plausible elliptical validation region V with a *gate threshold*, γ, is set up at every sampling time around the predicted measurement and is used to select believable measurements. Measurements from one target can fall in the validation region of the neighboring target and is *persistent interference*. All feature variables that carry information useful for discerning the correct measurement from the incorrect ones are assumed to be included in the measurement vector. The MFBA approach differs from conventional algorithms in how feature measurements are used in the estimation of the kinematic state to the correct target. Figure 4 shows the tradeoffs that are determined from the resolution level. The coarsest level uses kinematic feature information and is similar to the Probability Data Association Filter (PDAF). When identification features are employed, the learned feature which best discriminates between targets is called from each platform and fused. If a positive ID has not been performed, the next most discriminating feature is called from each sensor. The algorithm terminates the process either after all the features have been used or a measurement sequence is updated. Thus, the simultaneous decision of tracking and ID is one of evidential reasoning where the final decision is an association of the correct kinematic measurement to the fused set of features which results in the highest believable target type.

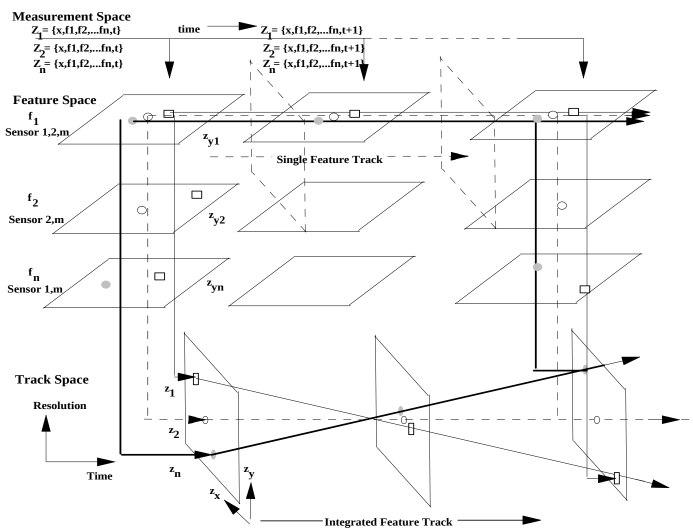

Figure 4. Multitarget- Multilevel feature Tracking.

Note, from Figure 4, if only the kinematic feature information is used a data association error could result from closely spaced measurements in a time constrained decision making process. However, if different features are utilized, assuming that the detection of these features are available in a timely manner as opposed to continuously sampling at the same coarse level, then the ID features can be fused together to associate the correct target type with the correct measurement. Thus, simultaneously associating multiple-level target and kinematic features results in higher belief of true measurement-to-target value and reduces the kinematic validation region.

4.2 Multiple Model Tracking Belief Filter

One of the key links between tracking and identification is the ability of the tracking filter to accurately position the identification sensor. The HRR data used for the implementation of the algorithm requires a link between pose information. *Pose* information consists of a depression angle and an aspect angle. The depression angle is related to the sensor position and aspect angle can be determined from the HRR profile. While Layne [8] uses the entire length of the HRR profile as the aspect angle, we utilize the distance between the peak features. Westercamp and Mitchell [9] have shown that the *peak* features in a HRR map can be used to classify objects.

Another deviation from the multiple model approach is that instead of just gathering HRR information, we assume that we have multiple targets in the search space, much as in the case of a moving target indicator (MTI) plot. In order to determine which measurements are plausible, we utilize the belief filtering approach [10] which uses evidential belief updates to allow for unknown target information.

The *Tracking Belief Filter* is an intelligent method which devotes attention to every believable measurement and cycles through measurement features until a target ID is reached. The filter assumes the *past* is summarized by an *approximate sufficient statistic* - state estimates (approximate conditional mean) and covariances for each target. Each measurement

$$z(k) = [x_t(k), f_1, \ldots f_n] \qquad (9)$$

is sequenced as it comes in as depicted in Figure 5, and the kinematic state and ID feature variables are separated. The algorithm starts by taking the highest level features, or those deemed to best discern a target, and uses it to ID the first object. The first feature is always assumed to be the kinematic state and available so that tracking can be performed at the coarsest resolution from a sequence of measurements. If the first fused identification feature, f_{11}, identify the target, then the probability update, $f_{11}\alpha_{11} \Rightarrow T_1$, is used as a sufficient statistic to identify that object. If the object is not discernable, the next feature f_{12} is used with its probability update to determine the belief in the first target. The procedure continues pulling features necessary to identify the first object from the multiple measurements until the feature best identifies the target, $\Sigma f_{11}\alpha_{11} \ldots f_{n1}\alpha_{n1} \Rightarrow T_1$. When a belief satisfies a threshold, the kinematic information is associated with that target ID belief. The final result is a feature matrix Γ, composed of feature-to-target probabilities. When the fused kinematic feature information is determined, a weight, β_1, from the track information is associated with the ID-feature information. If the final believable result is not above some desired threshold, this information is stored with this target and is put on the queue to see if the target can be identified given a process of elimination, thus capturing unknown targets.

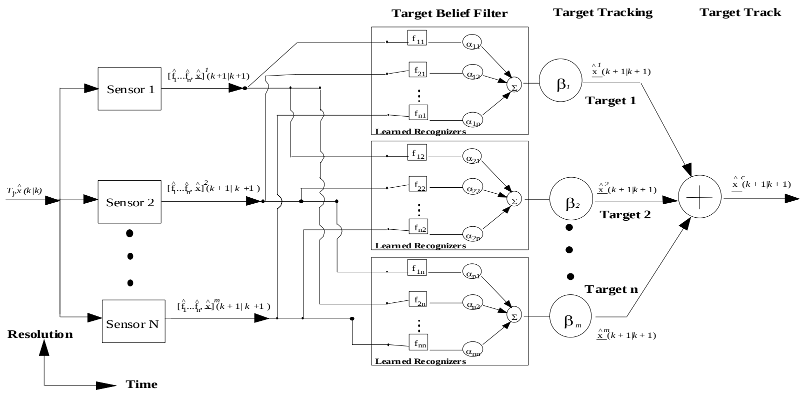

Figure 5. Feature-Recognition Tracking Model.

In the case of the TBF, multiple feature models are run for each target type known and for a fixed number of possible unknown targets. By using pose, we can match the position of the target with the aspect angle of the HRR sensor. The TBF predicts the next feature state, such as the aspect angle, and then determines which target is most plausible. Hence the target ID is based on the HRR peak feature measurements as well as the aspect angle. The aspect angle is determined from the azimuth and elevation angles of the sensor.

The feature-based approach extracts features from the HRR signature. The features are arranged into a feature vector, *x*,

$$\underline{x}_{k+1} = \Gamma_k \underline{x}_k + \Delta_k \underline{w}_k \tag{10}$$

where $\underline{x}_k = [f_1,..,f_k]^T$, where f_1 is the position and $f_2 \ldots f_n$ are ID features, $\Gamma_k = diag\,[\Gamma_1, .., \Gamma_n]$, and $w(t)$ is zero-mean mutually independent white Gaussian noise sequences with known covariances Q(t). The feature-state estimate and covariance propagation over time is:

$$\hat{x}_{k|k-1} = \Gamma\, \underline{x}_{k-1|k-1} \tag{11}$$

$$P_{k|k-1} = \Gamma\, \underline{P}_{k-1|k-1}\, \Gamma^T + \Delta_{k-1}\, Q\, \Delta^T_{k-1} \tag{12}$$

where P is the covariance matrix, $\Delta = diag\{\delta_1,...,\delta_n\}$, δ is the priority weight of the feature, and $Q = diag\{Q(f_1),..,Q(f_n)\}$.

4.3 Identification Belief Filter

The *ID belief filter* simulates the confirmation process people perform by predicting hypotheses in a frame of discernment, Θ. The frame of discernment consists of a collection of matched features, $\Theta = \cup\{f_2, .., f_n\}$. Only a subset of the entire combinations of features is possible. Thus, the belief set is a modification of Shafer's belief functions, explained in [10], to only include *a priori* learned set of feature combinations. The probabilistic fusion of extracted features is performed using Dempster's rule. Dempster's rule is modified to assign a priority, α, to salient features and discounted over time, γ, to reflect a change in feature saliency from previous images. A belief in a target hypothesis is propagated over time or a sequence of HRR signatures:

$$B_{Tk} = \frac{Hyp_i(\alpha_2 f_2, .., \alpha_n f_n)^*\gamma}{1 - C(\sum_{i=1}^{n} Hyp_i(\alpha_2 f_2,.., \alpha_n f_n))} \tag{13}$$

where C is the cognitive dissonance between mismatched features, T is the target type, i is the *a priori* hypothesis of feature combinations, and k is time. When the accumulated belief is greater than a confidence factor, the confirmation process is terminated and a decision is rendered for the target type.

The target-belief values are in a measurement matrix:

$$z_k = [\,Bel_k\,]\, x_k \tag{14}$$

where the propagation of the belief is performed much like a Kalman filter:

$$e_k = z_k - \hat{z}_{k|k-1} \tag{15}$$

$$w_k = P_{k|k-1}\, [Bel_k]^T\, [Bel_k\, P_{k|k-1}\, Bel_k^T + R]^{-1} \tag{16}$$

The *update* equations are:

$$P_{k|k} = P_{k|k-1} - w_k\, Bel_k\, P_{k|k-1} \tag{17}$$

$$x_{k|k} = x_{k|k-1} + w_k\, e_k$$

These generalized equations propagate belief-filtered, predicted feature measurements in time.

4.4 Fused Track and ID State Estimation

Assuming the targets conditioned on the past observations are *mutually independent*, the decoupled state estimation (filtering) of the *marginal association probabilities*, which are obtained from the joint probabilities, is obtained by summing over all joint events in which the marginal event of interest occurs. The conditional probability of the event (the association probability) is:

$$\beta_{jt} \triangleq P\{\theta_{jt}(k)|Z^k\}$$

$$= \sum_{\theta} P\{\theta|Z^k\}\hat{\omega}_{jt}(\theta) = \sum_{\theta:\theta_{jt}\in\theta} P\{\theta|Z^k\} \tag{18}$$

The algorithm decomposes the estimation with respect to the origin of each element of the *latest set* of validated measurements. Using the total probability theorem, with respect to the above events, the *conditional mean* of the state at time *k* can be written as:

$$\hat{x}(k|k) = \sum_{i=0}^{m(k)} \hat{x}_i(k|k)\, \beta_i(k) \tag{19}$$

where $x(k|k)$ is the update state *conditioned on the event that the i*th *validated measurement is correct.*

The state estimate, conditioned on measurement *i* being correct, is:

$$\hat{x}_i(k|k) = \hat{x}_i(k|k-1) + W(k)\nu_i(k) \tag{20}$$

$$\nu_i(k) = z_i(k) - \hat{z}(k|k-1) \tag{21}$$

$$W(k) = P(k|k-1)H(k)^T S(k)^{-1} \tag{22}$$

The *combined* state update equation, combined innovation, and covariance associated with the state are:

$$\hat{x}(k|k) = \hat{x}(k|k-1) + W(k)\nu(k) \tag{23}$$

$$\nu(k) = \sum_{i=1}^{m(k)} \beta_i(k)\,\nu_i(k) \tag{24}$$

$$P(k|k) = \beta_o(k)P(k|k\text{-}1) + [1-\beta_o(k)]P^c(k|k) \tag{25}$$

5. Initial Results

The MFBA track and ID method is evaluated with a Monte Carlo simulation and the performance metric is normalized probability of state error. As detailed in the Figures 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.

6. Discussion & Conclusions

Conventional measurement tracking techniques have difficulty in identifying targets when the measurement data is close together. The MFBA algorithm, which uses the feature measurements, identifies the correct targets and assigns measurements to the targets. In the presence of clutter, the novel algorithm warrants useful attention in

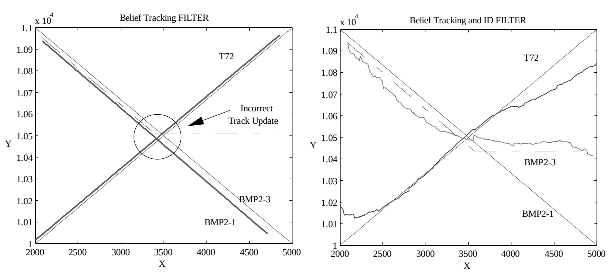

Figure 7. Measurement Tracking.

that it utilizes available processing capabilities of the sensor. If at first it does not succeed, it further focuses its attention on better discerning characteristics of the target as opposed to repeated unreliable measurements. By cycling through different feature levels, the algorithm shows promise for multiplatform-multisensor life-threatening situations in which survivability is required for mission completion. Additionally, when the situation is not life-threatening, then either track or ID modes can be used to aid a pilot. The MFBA can be utilized in a time-constrained scenario to get a general target location and a positive ID to avoid threatening and/or track numerous approaching targets.

This research included training a belief classifier using the association learning for feature recognition to guide an imperfect sensor or a perfect sensor in the presence of clutter to identify targets in a region. In a series of simulation experiments, the MFBA performed well resulting in a desirable solution, and at a faster rate than conventional mutlitarget-multisensor tracking methodologies. 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 can be modeled that are not readily handled by current tracking algorithms.

Acknowledgments

The first author would like to thank the Math and Geosciences Directorate of AFOSR for a grant 2312R1 that supported this research. Additionally, we would like to thank Jeff Layne, John Westercamp, and Rick Mitchell for their helpful comments.

References

[1] R. Popoli, "The Sensor Management Imperative", Chapter 10 in *Multitarget-Multisensor Tracking: Advanced Applications*, Vol. II, Y. Bar-Shalom, Ed., Artech House, 1992.

[2] E. Blasch and R. Malhotra, "Learning Sensor Detection Policies," *Pro. of IEEE NAECON*, Dayton, OH, July 1997, pp. 769-776.

[3] Y. Bar-Shalom and X. Li, *Mutitarget-Multisensor Tracking: Principles and Techniques*, YBS, New York, 1995.

[4] Z. Ding and L. Hong, "Decoupling probabilistic data association algorithm for multiplatform multisensor tracking," *Optical Engineering*, ISSN 0091-3286, Vol. 37, No. 2, Feb. 1998.

[5] K. Kastella. "Joint multitarget probabilities for detection and tracking," *SPIE AeroSense '97*, April 21-25, 1997.

[6] M. Efe and D. Atherton, "A Tracking Algorithm for both Highly Maneuvering and Non-maneuvering Targets," CDC '96, San Diego, CA, 1997, pg. 3150 – 3155.

[7] E. Libby, "Application of sequence comparison methods to multisensor data fusion and target recognition," Ph.D. Dissertation, AFIT, June 1993.

[8] J. Layne, "Automatic Target Recognition and Tracking Filter," *SPIE AeroSense – Small Targets*, April 1998.

[9] R. Mitchell and J. Westerkamp, "Statistical Feature Based Target Recognition," NAECON, 1998, pp. 111-118.

[10] E. Blasch and J. Gainey, "Feature Based Biological Sensor Fusion," *Intl. Conference on Info. Fusion*, 1998, pp. 702-709.