Target identification with Bayesian networks in a multiple hypothesis tracking system

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Abstract. A multisensor fusion algorithm that integrates model-based target identification (ID) and multiple-hypothesis tracking (MHT) is described. The algorithm augments the target state representation to include ID information and to manipulate the new target state. The major innovation of the algorithm is using Bayesian networks to modify the hypothesis-evaluation process by taking into account target ID. This research was conducted as part of a larger effort to design a decision-theoretic sensor management system. In the system, two types of sensors, electronically scanned radar (ESA) and IR search and track (IRST) are assumed to be available. The ESA radar is modeled to have search and update capabilities as well as three radar identification modes: ultra-high-resolution radar (UHRR), radar signal modulation (RSM), and radar electronic support mode (RESM). A Bayesian network is used to model the detection and observation processes for these ID techniques and compute the association likelihoods between measurements and tracks.

Subject terms: sensor fusion; Bayesian networks; multiple hypothesis tracking systems.

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1 Introduction

Tracking and fusion with multiple sensors has attracted a great deal of recent attention.[1–3] It deals with integration and correlation of data from various sources to arrive at an overall assessment of the situation. Difficulties in performing multisensor tracking and fusion include not only ambiguous data, but also disparate data sources. First, the identity of objects responsible for each individual data set is unknown, so there is uncertainty as to how to associate data from one sensor to those of another sensor. Second, the data sources may include various active and passive sensors such as radar, IR, and acoustic sensors. The tracking and fusion problem is further complicated by the facts that the target may not be detected by some sensors due to the variation of signals and the sensor characteristics, and dense false alarms and clutters may be present that are not easily distinguishable from the true target measurements.

It is well known that the performance of multiple-hypothesis approaches for multitarget tracking are near-optimal and have gained popularity[1,3,4] since the pioneer work of Reid.[5] In these approaches, all feasible data association hypotheses between measurements and targets are formed, evaluated, and maintained. This paper deals with the developing of an algorithm for incorporating target identification (ID) into a multiple-hypothesis tracking (MHT) system for multiple sensor environment. Specifically, the target state representation is augmented to include ID information and the hypothesis evaluation is modified by taking into account the target ID using Bayesian network techniques. The Bayesian network model is a part of a model-based identification (MBID) component, which is a part of a larger effort to design a decision-theoretic sensor management system.[6] The goal of the MBID component is to show the benefits of sensor management with MBID.

It is assumed that in the system, there are two types of sensors: electronically scanned radar (ESA) and IR search and track (IRST). In addition to the regular search and update capabilities, the ESA radar is modeled to have three identification modes: ultra-high-resolution radar (UHRR), radar signal modulation (RSM), and radar electronic support mode (RESM). Since the radar detection and observation processes are fairly complicated and can not be easily expressed in a simple form, a Bayesian network is used to model the processes and compute the association likelihoods as well as manipulate the target state distribution. In the system, a centralized fusion architecture is assumed, i.e., data collected from multiple sensors are pooled together in a central site where they are combined.

This paper is organized as follows. Section 2 briefly reviews the MHT system, and Sec. 3 describes new target state representation and equation updating. Section 4 presents the Bayesian network inference module and the integrated system. Some concluding remarks are given in Section 5.

2 Multiple Hypothesis Tracking System

In this section, we briefly describe a general theory of multiple-hypothesis multitarget tracking. Suppose we are given a series, $(Z_1, Z_2, ...)$, of data sets. Each data set is a set of measurements taken from a sensor s_k at the same time t_k: Thus, each data set Z_k is in turn a finite sequence of measurements, i.e., $Z_k = (y_1^k, \ldots, y_{M_k}^k)$, where M_k is the number of measurements contained in the data set Z_k. The problem of multitarget tracking is in general, given a cumulative collection of data sets, e.g., $Z^k = (Z_1, Z_2, \ldots, Z_k)$,

(1) to compute the *a posteriori* probability of detected targets in Z^k, i.e., the number of real targets that have been detected at least once in Z^k and have generated some measurements in Z^k, and (2) to obtain *a posteriori* probabilistic distributions of target states.

At this moment, the only known theoretically consistent way of expressing the above two *a posteriori* probabilistic assessments is through tracks and data-to-data association hypotheses, as defined later. First, let us define the measurement index set $j_k = \{1,\ldots,M_k\}$ for each k, and the cumulative collection $J^K = \{j_k \times \{k\}; k \leq K\}$ of measurement index sets. Then, a track at k, or equivalently, on Z^k or J^k, is any subset of the cumulative collection J^k of measurement index sets. For example, a track, $\tau = \{(j_1,1),(j_3,3)\}$ on J^3 hypothesizes a target detected at the first scan, $k=1$, as the j_1'th measurement, not detected at the second scan, $k=2$, and then detected again at the third scan, $k=3$, as j_3'th measurement. Then a data-to-data association hypothesis at k, or equivalently on Z^k or J^k, is merely a set of tracks at k. A data-to-data association hypothesis is referred to simply as a ''hypothesis'' from now on. Assuming no split or merged measurements, we can exclude (1) tracks that have two or more measurements in a single data set and (2) hypotheses containing overlapping tracks.

Under a certain set of assumptions, including the assumptions of independent and identically distributed (i.i.d.) targets and a Poisson distribution for the *a priori* number of targets, we can show that[4]

$$\mathrm{Prob}\{\Lambda|Z^k\} = \frac{1}{c}\,\mathrm{Prob}\{\overline{\Lambda}|Z^k\}\prod \{L(y|\overline{\tau})\}\prod \{M(\overline{\tau})\} \times \prod \{\beta_{\mathrm{NT}}(y)\}\prod \{\beta_{\mathrm{FA}}(y)\}, \tag{1}$$

where Z^k is the cumulative collection of data sets up to and including the k'th data set Z_k, Λ is an arbitrary hypothesis at k, and C is the normalizing constant. Given a track τ on Z^k, $\overline{\tau}$ is a track that is on Z^{k-1} and a unique predecessor of the track τ. Given a hypothesis Λ on Z^k, $\overline{\Lambda}$ is a hypothesis that is on Z^{k-1} and a unique predecessor of Λ. Here $L(y|\overline{\tau})$ is the likelihood of a measurement in data set Z_k having value y being associated with an existing track $\overline{\tau}$; $M(\overline{\tau})$ is the likelihood of an existing track $\overline{\tau}$ not being associated with any measurement in the current data set Z_k, $\beta_{\mathrm{NT}}(y)$ is the likelihood of a measurement in Z_k with value y originating from a newly detected target, and $\beta_{\mathrm{FA}}(y)$ is the likelihood of a measurement in Z_k, with value y being a false alarm. The four terms in Eq. (1) are explained in more detail in the following.

The first term $L(y|\overline{\tau})$ is a mixture of a conditional probability and the density of conditional probability distribution, in the sense that $\int_{\Delta Y} L(y|\overline{\tau})\,dy$ is the probability of a target hypothesized by a track τ being detected and producing a measurement y in ΔY. This likelihood is given by

$$L(y|\overline{\tau}) = \int p_M(y|x)p_D(x)p(x,t_k|\overline{\tau},Z^{k-1})\,\mathrm{d}x, \tag{2}$$

where $p_M(y|x)$ is the density of the probability distribution of measurement value y given a target state x; more precisely, $\int_{\Delta Y} p_M(y|x)\,\mathrm{d}y$ is the conditional probability of a target at state x, given its being detected in the data set Z_k, generating a measurement with value y in ΔY. Also, $p_D(x)$ is the probability of a target at state x being included (detected) in the data set Z_k, $p(x,t_k|\overline{\tau},Z^{k-1})$ is the density of the target state distribution of a target hypothesized by the track $\overline{\tau}$, evaluated at the time-prediction distribution. In the linear Gaussian case where we assume that the target state distributions of all the old tracks $\overline{\tau}$ have Gaussian representations, as

$$p(x|\overline{\tau}) = [\det(2\pi\overline{V})]^{-1/2}\exp(-\tfrac{1}{2}\|x-\overline{x}\|^2_{\overline{V}^{-1}}). \tag{3}$$

Then it follows from the linearization of nonlinear measurement equations that the measurement-to-track association likelihood is

$$L(y|\overline{\tau}) = P_D(x)[\det(2\pi\mathbf{S})]^{-1/2}\exp(-\tfrac{1}{2}\|y-\overline{y}\|^2_{S^{-1}}), \tag{4}$$

where $\overline{y}$ is the projection of target state estimate $\overline{x}$ onto the sensors' measurement space, $\mathbf{S}$ is the innovations variance matrix defined by $\mathbf{S} = \mathbf{H}\overline{V}\mathbf{H}^T + \mathbf{R}$, where $\mathbf{H}$ is the partial derivative matrix of the sensor measurement to the target state and $\mathbf{R}$ is the sensor measurement error covariance matrix.

The second term $M(\overline{\tau})$ is the probability of a target hypothesized by track $\overline{\tau}$ not being detected in the data set Z_k, when the predicted track is well inside the sensor field of view (FOV), given by

$$M(\overline{\tau}) = \int [1-p_D(x)]p(x,t_k|\overline{\tau},Z^{k-1})\,\mathrm{d}x \approx 1-P_D(x). \tag{5}$$

The third term $\beta_{\mathrm{NT}}(y)$ is the density of newly detected targets at y, i.e., $\int_{\Delta Y}\beta_{\mathrm{NT}}(y)\,\mathrm{d}y$ is the expected number of targets that have not been detected in the past data sets in Z^{k-1} but are detected (for the first time) in the current data set Z_k as measurements with values y in ΔY. This is given by

$$\beta_{\mathrm{NT}}(y) = \int p_M(y|x)p_D(x)\beta_{\mathrm{UDT}}(x,t_k|Z^{k-1})\,\mathrm{d}x, \tag{6}$$

where $\beta_{\mathrm{UDT}}(x,t_k|Z^{k-1})$ is the density of targets that are undetected in each of the past data sets, $Z_1,\ldots,Z_{k-1}$, in the target state space at the time t_k, i.e., $\int_{\Delta X}\beta_{\mathrm{UDT}}(x,t_k|Z^{k-1})\,\mathrm{d}x$ is the expected number of targets that have not been detected previously (prior to the data set k) and whose state x is in ΔX. The calculation of β_{NT} is not straightforward. A simple approximation is to assume a uniform undetected target density, then

$$\beta_{\mathrm{NT}} = \frac{v_T}{\Pi\,\mu(\mathrm{FOV}_i)}, \tag{7}$$

where v_T is the expected number of targets appearing in the given region within a given time period, and $\mu(\mathrm{FOV}_i)$ is the volume of the field of view for the measurement component i.

The fourth term $\beta_{FA}(y)$ is the density of false alarms included in the current data set Z_k, i.e., $\int_{\Delta Y}\beta_{FA}(y)dy$ is the expected number of false alarms included in the region ΔY: With uniform assumption,

$$\beta_{FA}=\frac{v_{FA}}{\Pi\mu(\mathrm{FOV}_i)}, \tag{8}$$

where v_{FA} is the expected number of false alarms.

We can call each of the four kinds of factors appearing in Eq. (1) the track-to-measurement association likelihood function. In short, the general multihypothesis multitarget tracking theorem says, under a certain set of assumptions, the posterior probability of every hypothesis at each data set can be calculated as a normalized product of appropriate track-to-measurement association likelihood functions.

Equation (1) is in a recursive form, and to close the recursion, we need the following set of updating equations, which update the states of the tracking algorithm. For every hypothesis Λ and every $\tau\in\Lambda$, if a track is associated with a measurement, then

$$p(x,t_k|\tau,Z^k)=L(y|\overline{\tau})^{-1}p_M(y|x)p_D(x)p(x,t_k|\overline{\tau},Z^{k-1}), \tag{9}$$

otherwise

$$p(x,t_k|\tau,Z^k)=M(\overline{\tau})^{-1}[1-p_D(x)]p(x,t_k|\overline{\tau},Z^{k-1}). \tag{10}$$

The detection probability function $p_D(x)$ is a combination of the FOVs in each measurement component and the given detection characteristics. When a target is updated, assuming the target state distribution is not affected too much by the function $p_D(x)$, and therefore, is in Gaussian case, they become the application of the Kalman filter or extended Kalman filter to

$$\hat{\mathbf{x}}(k|k)=\hat{\mathbf{x}}(k|k-1)+W(k)[y(k)-\hat{y}(k|k-1)], \tag{11}$$

with

$$W(k)=\Sigma(k|k-1)\mathbf{H}'(k)S(k)^{-1} \tag{12}$$

and

$$\begin{aligned}\Sigma(k|k)&=[I-W(k)\mathbf{H}(k)]\Sigma(k|k-1)\\&=\Sigma(k|k-1)-W(k)\mathbf{S}(k)^{-1}W(k),\end{aligned} \tag{13}$$

which update the mean vector to $\hat{\mathbf{x}}(k|k)$ and the estimation error covariance matrix to $\Sigma(k|k)$ from the extrapolated mean vector $\hat{\mathbf{x}}(k|k-1)$ and the extrapolated covariance matrix $\Sigma(k|k-1)$, which are obtained as

$$\begin{aligned}\hat{\mathbf{x}}(k|k-1)&=\mathbf{F}\hat{\mathbf{x}}(k-1|k-1),\\ \Sigma(k|k-1)&=\mathbf{F}\Sigma(k-1|k-1)\mathbf{F}+\mathbf{Q},\end{aligned} \tag{14}$$

where $\mathbf{F}$ is the target transition matrix and $\mathbf{Q}$ is the process noise covariance matrix.

It is clear from Eqs. (9) through (14) that this theory of multitarget tracking is actually an extension of general state estimation or filtering theory.

3 Target State Representation for Identification

To compute the track-to-measurement association likelihood for a MHT system, the target state space and representation need to be defined. A target state distribution is a probability distribution on a target state space. To incorporate classification, the target state space can be formally described as

$$\chi=\chi_G\times\chi_C, \tag{15}$$

which is a direct product of the space χ_G for the geolocational states and the target classification space χ_C. Typically, the geolocational state space χ_G is the 3-D space for target location and velocity. The target state space component χ_C is concerned with target classification and can be represented as

$$\chi_C=\bigcup_{c\in C}\chi_c, \tag{16}$$

where C is the set of all the target classes and χ_c is the classification space* for a particular target class $c\in C$.

Finally, assuming a certain independence among the state components, the density function of a probability distribution on the abstract state space can be defined as

$$P(X)=P(X_G,X_C)=P_G(X_G)P_C(X_C), \tag{17}$$

where $P_G(X_G)$ represents a geolocational probability distribution and $P_C(X_C)$ is the classification distribution.

As described earlier, two types of manipulations are needed for target state in a MHT system, namely, extrapolation and updating. For geolocational components, a standard Kalman filter or an extended Kalman filter can be used, as given in Eqs. (11) to (14). For classification components, since it is a static state space, no dynamic extrapolation operation is needed. In fact, only updating operation and the corresponding association likelihood are needed in the MHT processing. Similar to Eqs. (9) and (10), the updating equation for the classification components can be written as

$$\begin{aligned}P_C(X_C,t_k|\tau,Z^k)=&L_C(y_j|\overline{\tau})^{-1}p_M(y_j|X_C)p_D(X_G,X_C)\\&\times P_C(X_C,t_k|\overline{\tau},Z^{k-1}),\end{aligned} \tag{18}$$

for the track with associated measurement y_j, and

$$\begin{aligned}P_C(X_C,t_k|\tau,Z^k)=&M_C(y_j|\overline{\tau})^{-1}[1-p_D(X_G,X_C)]\\&\times P_C(X_C,t_k|\overline{\tau},Z^{k-1}),\end{aligned} \tag{19}$$

for the track with no associated measurement. In Eqs. (18) and (19), $p_D(X_G,X_C)$ is the detection probability of the target and is a function of both geolocational and classification components of the target state,

$$P_C(X_C,t_k|\overline{\tau},Z^{k-1})=P_C(\overline{X_C},t_{k-1}|\overline{\tau},Z^{k-1}), \tag{20}$$

*For example, in our scenario, we may have C={blue1 blue2 red1 red2 neutral unknown}.

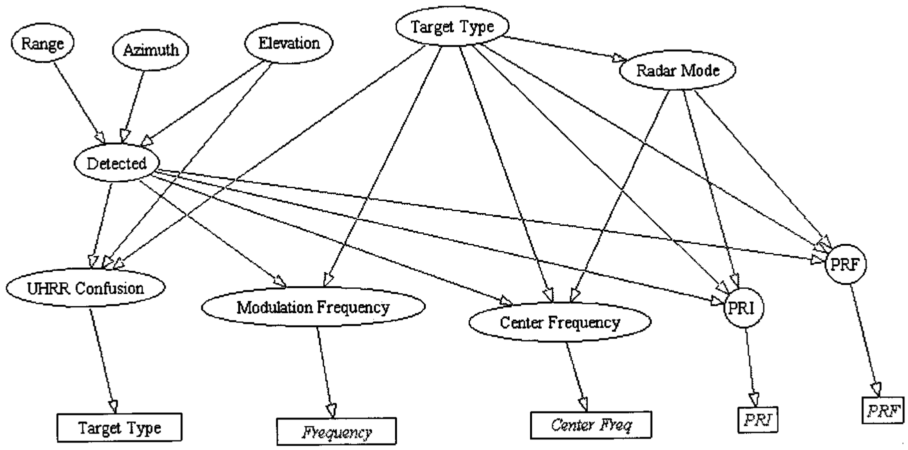

Fig. 1 MBID module—a BN.

is the extrapolated state that is equal to the previous updated state for the reason explained earlier, and

$$L_C(y_j|\overline{\tau})=\sum_C p_M(y_j|X_C)p_D(X_G,X_C)P_C(X_C,t_k|\overline{\tau,}Z^{k-1}) \tag{21}$$

and

$$M_C(y_j|\overline{\tau})=\sum_C [1-p_D(X_G,X_C)]P_C(X_C,t_k|\overline{\tau,}Z^{k-1}) \tag{22}$$

are the corresponding association likelihoods.

For radar and IR sensors, the detection and observation mechanism are fairly complicated and in general Eqs. (18) to (22) can not be easily expressed in simple forms as in Eqs. (11) to (14). In fact, most of the time, for classification components, we do not observe the target state directly, rather, indirect observation such as frequency and pulse repetition interval (PRI) are used to update the target state distribution. Therefore, instead of implementing Eqs. (18) and (19) and (21) and (22) algebraically, a Bayesian network is used to model the detection and observation processes and to compute the association likelihoods as well as update the target state distribution.

4 Bayesian Network Inference and the Integrated System

The track-to-measurement likelihoods that are essential to multiple hypothesis processing must be computed efficiently. The hierarchical nature of the target model suggests a highly flexible and efficient method in terms of Bayesian networks (BNs). A BN is an annotated acyclic directed graph that encodes probabilistic relationships among distinctions of interest in an uncertain-reasoning problem. The representation formally encodes the joint probability distribution for its domain, yet includes a human-oriented qualitative structure that facilitates a user to incorporate the probabilistic models.

In a Bayesian network, each node in the graph is a random element, and the arc between two nodes indicates a potential stochastic dependence between the two random elements represented by the two nodes. The qualitative relationships represented by incoming arcs to a state node is quantified as a conditional probability distribution. For a MHT system, the BN is used to relate the targets states to the detections at the sensors. Each measurement node represents the detected measurement from a source at a given sensor. The conditional probabilities depend on the propagation from the target to the sensor, array gain, detection thresholds, etc. Other information such as relative geometry between target and sensor, the strength of the target, and the transmitted energy can also be summarized in the conditional probability of the received measurement given the target state.

In addition to the convenient and flexible representation, a major benefit of using BNs is the existence of many powerful probabilistic inference algorithms developed recently. The goal of inference is to update beliefs in particular states of interest in the light of the current state of information and new evidence about a situation. The updated beliefs are known as posteriors, while the state of information before the evidence arrives is known as priors. In the context of the MHT approach, the inference algorithms can also be used to compute the likelihoods of given track-to-measurement associations. Many inference algorithms for BNs have been developed. They include the distributed algorithm,[7] the influence diagram algorithm,[8] the evidence potential algorithm,[9] simulation algorithms,[10,11] and the symbolic probabilistic inference (SPI) algorithm.[12] The simulation and SPI algorithms are the most flexible and efficient ones.

In the system, it is assumed that three radar identification modes are available: UHRR, RSM, and RESM. UHRR is an active technique and is basically an imaging technique that will be able to identify features of an airplane and therefore infer the target type. RSM is an active technique that can detect a target feature-modulation frequency. RESM is a passive technique that can observe the characteristics of the target's radar emissions. Based the observed features of the radar signal, the MBID system will infer a radar mode that will in turn be an evidence for a target type.

Figure 1 shows the BN that contains all three identification modules. Note that at any given moment, only one module can be active. In other words, only one type of evidence can be attached to the network. In the figure,† the UHRR module is represented by the node ''UHRR Confusion,'' RSM is represented by the node ''Modulation Frequency,'' and RESM is represented by the remaining three nodes, ''Center Frequency,'' ''PRI,'' and ''PRF'' (pulse repetition frequency). Note that in all three radar modes, the observation is dependent on the probability of detection represented by the node ''Detected.'' Probability of detection is a logistic curve as a function of target range and aspect angle. The measurements from the three radar modes can either be discrete or continuous values. For example, the observation of UHRR is the actual target type, which can only be one of the given values. On the other hand, the observations for other radar modes have continuous values and can assume any value within the defined distribution. The detailed description of all the conditional probability tables and evidence distributions are given in the Appendix.

The purpose of building the BN is, again, to compute the updated track and the association likelihood given an extrapolated track and a measurement. To compute the updated track state distribution is rather straightforward. First, substitute the given extrapolated track state distribution $P_C(X_C, t_k | \overline{\tau, Z^{k-1}})$ into the prior probability distribution of the root node ''Target Type,'' i.e., the prior probability density function (pdf) of the target classification is the current extrapolated target classification pdf. For a given measurement y_j, attach it to the leaf node of the corresponding radar mode, then execute a updating algorithm (SPI or simulation algorithm[10–12]) to compute the *a posterior* distribution of the node ''Target Type'' given that measurement. The result is the pdf of the updated track and is the first element to be computed.

To compute the association likelihood between a given track and a measurement is, however, more complicated. We use a simple two-step inference algorithm.[13] The idea is to ''predict'' the observation distribution using forward inference given a target type, then compute the likelihood based on the difference between the predicted observation and the actual observation. For a particular set of observations, the first step is to do forward inference from the root nodes for each possible combination of root node values to the observation nodes. This step can be done either with simulation method or the SPI algorithm depending on the network configuration. In our network, since all nodes are discrete except for the leaf nodes, the SPI algorithm can be used to compute the ''prior'' distribution of observation nodes given each root node configuration. However, in general, when a network contains non-Gaussian continuous nodes, simulation method is the only way to do forward inference.

The second step is to compute the likelihood based on the observed evidences. If the observation node is a discrete variable, this step can be done by selecting appropriate entries from the prior pdf of the observation node, which corresponds to the specific observation. If the observation node is a continuous variable, then first of all, the prior pdf of the observation needs to be represented approximately by a unimodal or multimodal Gaussian distribution, the likelihood is then computed based on the degree of closeness between the actual observation and the predicted observation.

†In the figure, random variables are represented by oval nodes, and evidences by rectangle boxes.

T \ *M*	B_1	B_2	R_1	R_2	N_1	*Unk*	*Und*
B_1	.63	0	0	0	0	0	.37
B_2	0	.63	0	0	0	0	.37
R_1	0	0	.63	0	0	0	.37
R_2	0	0	0	.63	0	0	.37
N_1	0	0	0	0	.63	0	.37
Unk	0	0	0	0	0	.63	.37

Fig. 2 Conditional pdf table for *P*(modulation frequency | target type).

For example, for the BN shown in Fig. 1, if modulation frequency is observed, first do the forward inference process from target type to modulation frequency. This is to compute the prior pdf of modulation frequency given each target type value. Since all nodes are discrete except evidences, this can be done exactly and easily by computing the conditional probability *P*(modulation frequency | target type) using SPI algorithm. The result is a conditional pdf table such as the one shown in Fig. 2.

The second step is to account for actual observation. In the network given in Fig. 1, the evidence node ''Frequency'' attached to the ''Modulation Frequency'' is a continuous node. A Gaussian distribution with appropriate mean and variance is assumed to be given (see the Appendix for details) for each value of ''Modulation Frequency.'' When a measurement is received, the value is checked against each Gaussian distribution and a set of likelihoods is computed based on the Gaussian formula, namely,

$$\mathbf{L}_{ij} = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left[-\frac{(y_j - \eta_i)^2}{2\sigma_i^2} \right], \tag{23}$$

where η_i and σ_i are mean and standard deviation of the gaussian distribution corresponds to each value *i* of the node ''Modulation Frequency.'' Given the table in Fig. 2 and the likelihood vector obtained by Eq. (23), the last step is to calculate the inner product of each row vector of the table with the likelihood vector. This is to apply a weighted sum to the prior distribution based on the evidence. The result is a vector of likelihoods each for a value of target type, the summation of those values in the vector is the measurement-to-track association likelihoods and final result to be returned. For example, if the likelihood obtained based on Eq. (19) is

$$\begin{array}{ccccccc} B_1 & B_2 & R_1 & R_2 & N_1 & Unk & Und \\ 0.0388 & 0 & 0.0299 & 0 & 0 & 0.006 & 0, \end{array} \tag{24}$$

then the final result is

$$\sum_k \sum_i TM(k,i)\mathbf{L}(i) = 0.0471 \tag{25}$$

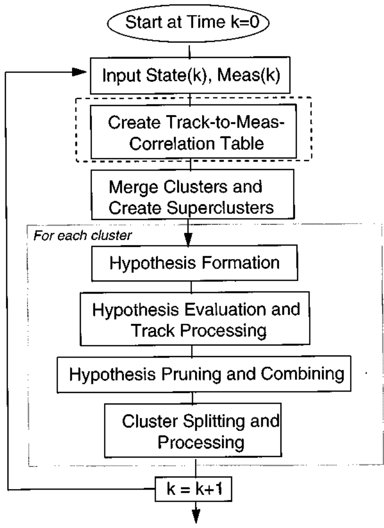

Fig. 3 An MHT system flow diagram.

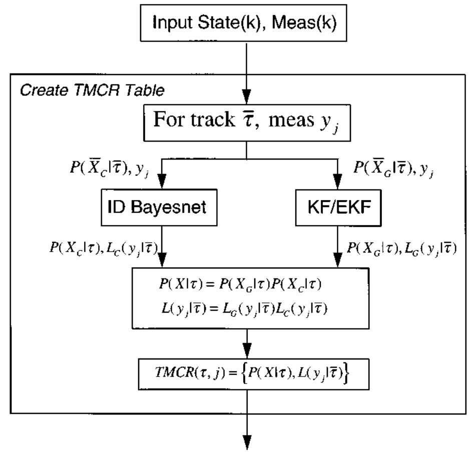

Fig. 4 Processing flow for likelihood calculation and track update.

where $TM(k,i)$ represents the table given in Fig. 2 and $\mathbf{L}(i)$ is the vector given in Eq. (24).

In the following, a brief description of the integrated system together with a step by step processing example are given to illustrate the fusion procedure. An MHT system can be considered as a machine that generates and operates on structured data, i.e., clusters, hypotheses, and tracks. A standard flow diagram of a MHT system is shown in Fig. 3. As indicated in the figure, in a MHT processing cycle, based on the state (hypotheses, tracks, etc.) and measurements at time k, a sequence of procedures are executed to produce the new state at time $k+1$. These standard procedures typically include forming a track-to-measurement correlation table (TMCR), forming new clusters, creating and evaluating new hypotheses, and pruning and combining hypotheses.

To incorporate MBID, as proposed in this paper, the only required modification is the TMCR module, as indicated by the dashed-line box in Fig. 3. Specifically, when filling the TMCR table, a step-by-step explanation of the processing procedure is as given shortly.

Assuming the input to the MHT system at time k include a set of hypotheses State(k) and a set of measurement Meas(k). To form a TMCR table is to create a correlation between all tracks in the set of hypotheses and the set of measurements. Each entry in the table contains a correlation likelihood between a extrapolated track $\bar{\tau}$ and a measurement y_j as well as the updated state description $p(X|\tau)$. Since each track contains both discrete and continuous state estimates, the two state space components of each track are processed separately.

1. For the continuous component, use standard Kalman filtering given by Eqs. (11) to (14).
2. For the discrete component, use the predefined BN, as described in Eqs. (18) to (22) and (23) to (25).
3. The resulting updated states are combined according to Eqs. (15) to (17), which multiplies a discrete and a continuous distribution into a mixed probability distribution. This is the first half of the entry to the TMCR table.
4. The corresponding likelihoods from processes 1 and 2 are multiplied to obtain the overall association likelihood for the second half of the entry in the TMCR table.

Figure 4 shows a detailed diagram of the TMCR module. Other than the TMCR module, the rest of the MHT process remains the same. Figure 5 shows a resulting TMCR table.

Together with a decision-theoretic approach, the algorithm has been implemented and integrated into a sensor management system. A major advantage of using the current approach is the flexibility of enabling users to change the model fairly easily. This can be done by modifying the

Meas#		0	1	2	$\cdots$	N_m
NewTrack	0	L_{00}	L_{01}	L_{02}	$\cdots$	L_{0N_m}
Existing	1	$L_{10}, p(X\|\bar{\tau}_1)$	$L_{11}, p(X\|\bar{\tau}_1, y_1)$	$L_{12}, p(X\|\bar{\tau}_1, y_2)$	$\cdots$	$L_{1N_m}, p(X\|\bar{\tau}_1, y_{N_m})$
Tracks	2	$L_{20}, p(X\|\bar{\tau}_2)$	$L_{21}, p(X\|\bar{\tau}_2, y_1)$	$L_{22}, p(X\|\bar{\tau}_2, y_2)$	$\cdots$	$L_{2N_m}, p(X\|\bar{\tau}_2, y_{N_m})$
	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
	N_t	$L_{N_t0}, p(X\|\bar{\tau}_{N_t})$	$L_{N_t1}, p(X\|\bar{\tau}_{N_t}, y_1)$	$L_{N_t2}, p(X\|\bar{\tau}_{N_t}, y_2)$	$\cdots$	$L_{N_tN_m}, p(X\|\bar{\tau}_{N_t}, y_{N_m})$
False Alarms			L_{F1}	L_{F2}	$\cdots$	L_{FN_m}

Fig. 5 Resulting TMCR table.

topology or parameters of the BN. By incorporating ID information, the ability of data association is enhanced significantly. We have tested the system with simulated data. As expected, the results indicated that, with the additional ID capability, not only does the average correct association between track and measurement increase, but the track qualities such as accuracy and track probability also improve. The proposed algorithm of using BNs to account for target ID in the MHT processing is shown to be quite reliable.

5 Discussion and Summary

We have developed a multisensor fusion algorithm that incorporates target ID into an MHT system. The algorithm augments the target state representation to include ID information and to manipulate the new target state. The major innovation of the algorithm is the use of BNs to modify the hypothesis evaluation process by explicitly taking into account target ID.

This research was conducted as part of a larger effort to design a decision-theoretic sensor management system. A BN is used to model the detection and observation processes for various radar ID modes and compute the association likelihoods between measurements and tracks. The algorithm has been implemented and integrated into a multisensor tracking and fusion system. A major advantage of using the current approach is the flexibility of modifying the Bayesian models to account for various potential environmental or sensor changes. One important future research direction is to develop automatic or semiautomatic learning methods to build the BN. These methods should be able to combine expert knowledge with data to produce network topology and parameters automatically. We have done some research in that area and preliminary results obtained so far are very promising.[14]

6 Appendix: BN Model description

The following tables contain the conditional probabilities of each variable given its parent in the BN shown in Fig. 1. They are compiled from domain expert knowledge.

6.1 *Target Type Prior Probability*

Target Type	Probability
B1	.2
B2	.2
R1	.2
R2	.2
N1	.1
UNK	.1

6.2 *UHRR Mode*

The feature of UHRR is an identification. We represent the conditional probability of a UHRR ID with the target type with a confusion matrix. The confusion matrix is indexed by relative target elevation (which we assume is known at the time of the UHRR action).

With the band at in plane $+-40$ deg in elevation:

	B1	B2	R1	R2	N1	UNK
B1	.95	0	0	0	0	.05
B2	0	.95	0	0	0	.05
R1	0	0	.95	0	0	.05
R2	0	0	0	.95	0	.05
N1	0	0	0	0	.95	.05
UNK	.02	.02	.02	.02	.02	.9

With the band at medium (40 to 80; -40 to 80):

	B1	B2	R1	R2	N1	UNK
B1	.8	.02	.1	.02	.02	.04
B2	.02	.7	.02	.14	.08	.04
R1	.1	.02	.8	.02	.02	.04
R2	.02	.14	.02	.7	.08	.04
N1	.02	.15	.02	.15	.6	.04
UNK	.04	.04	.04	.04	.04	.8

With the band at out of plane:

	B1	B2	R1	R2	N1	UNK
B1	.4	.07	.3	.07	.07	.09
B2	.1	.32	.1	.22	.16	.1
R1	.3	.07	.4	.07	.07	.09
R2	.1	.22	.1	.32	.16	.1
N1	.1	.2	.1	.2	.25	.15
UNK	.15	.15	.15	.15	.15	.4

6.3 *RSM Mode*

Logistic curve as a function of range and also of aspect angle:

Target Type	Modulation Frequency (mean, std. dev.)
B1	100, 10
B2	200, 20
R1	120, 10
R2	170, 15
N1	210, 10
UNK	150, 50

6.4 *RESM Mode*

For radar modes:

Radar Mode/ Target Type	B1	B2	R1	R2	N1	UNK
Off	.1	.1	.1	.1	.1	.1
VS	.225		.225			.125
TWS	.225		.225			.125
STT	.225		.225			.125
ID	.225		.225			.125
GMT		.3				.125
RBGM		.3		.9		.125
SAR		.3				.125
Weather						.125

For center frequency:

Radar Mode	Target Type	Center Frequency	Pulse Width	Pulse Rept. Freq.
Off				
VS	B1	10, .5	6, .01	100, 10
	r1	11, .5	5	110, 10
TWS	B1	10, .5	6	10, 1
	R1	11, .5	5	11, 1
STT	B1	10, .5	6	100, 10
	R1	11, .5	5	110, 10
ID	B1	10, .5	6	100, 10
	R1	11, .5	5	110, 10
GMT1	B2	10, .5	6	1, .1
RBGM	B2	10, .5	6	1, .1
	R2	10.5, .5	5	1, .1
SAR	B2	10.5, .5	5	1, .1
Weather	N1	5, .5	10	10, 1

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