Set Theory Correlation Free Algorithm for HRRR Target Tracking

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ABSTRACT

One challenge of simultaneous tracking and identification of targets is the fusion of continuous and discrete information. Recently a few fusionists including Mahler [1] and Mori [2] are using a set theory approach for a unified data fusion theory which is a correlation free paradigm [3]. This paper uses the set theory approach as a basis for a method of fusing kinematic-continuous data and identification-discrete feature information. The set of features are high range resolution radar range-bin locations and amplitudes which are collected over a small aperture and a scrambled method is used to order a feature set. Once features are ordered, a recursive belief filter operates in feature space to combine track and identification measurements. The intersection of track and identification methods results in a simultaneous tracking and identification algorithm which accumulates evidence for belief in targets and rules out non-plausible targets

1.0 Introduction

Multitarget tracking in the presence of clutter has been investigated through the use of data association algorithms [4] such as the *joint-probability data association* (JPDAF). Likewise, other multisensor fusion algorithms have focused on tracking targets from multiple look sequences such as the *multiresolution wavelet-based* approach formulated by Hong [5]. One inherent limitation of current algorithms is that the information used to track targets is based only on kinematic measurements. Recently, algorithms have been proposed for feature-aided tracking. Feature-aided tracking uses object features to help discern targets in the presence of clutter such as high-range resolution radar(HRRR) [6]. Typically an image analyst is required to abstract target type data to update tracks. Once the human has a belief or a hypothesis in the target type, the tracking algorithm can be updated. *Multiple Hypothesis Tracking* (MHT), developed by Reid [7] and based on a multiple hypothesis estimation (MHE) [4], might expand the set of hypothesis to an unmanagble number. In order to implement the algorithm, hypothesis management is typically performed. Using target feature-set information reduces the number of target hypotheses.

Three *HRR tracking and classification algorithms* have been proposed. In 1996, Stone [8] proposed a non-linear *Bayesian likelihood ratio tracker* (LRT) with an evidential accrual and data fusion approach to control the number of targets and compared it to the MHT algorithm. Following this work, Metron, applied the approach to shipboard HRR [9]. For the second method, Jacobs and O'Sullivan added tracking to their Bayesian HRR ATR algorithm and computed *joint likelihood probabilities* [10] with applications. Kastella has adapted the work of Jacobs and uses scatter-centering models for a nonlinear joint tracking and recognition algorithm based on joint probability density functions, but much of his work is simulated [11]. Kastella and Musick are using a *joint-multiprobability* algorithm, or JMP, to associate classifications and track updates. The third algorithm is that of Layne [12,13] - an *automatic target recognition and tracking filter* (ATRF) in a multiple model estimator (MME) approach for HRRR signatures. Layne's work can be considered an extension of the MME from Libby and Maybeck [14], who simulated an HRRR tracker. These approaches, although influential in this work, rely on the Bayes' rule for identification where the most probable target is selected. 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 or targets not trained for classification. We seek to expand on these tracking and ID algorithms for HRRR signatures, by allowing for the capability to discern unknown relevant targets and reject non-plausible targets. The method used to augment track-association uncertainties is a set-theory approach which helps enhance track quality.

Many tracking algorithms utilize information from multiple sources that measure the target at a single resolutional level. Results have proven well for distributed filtering of multiresolutional signals [15,16]. The ability to process

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the measured signals at a variety of resolutions is applicable to many situations, e.g. surveillance systems, where the observer could choose to look at the fine details at the highest resolution or a coarse control at the lowest resolution. For this paper, we use a multiresolutional approach where coarse measurements are the kinematic track information and the fine measurements consist of the HRRR feature measurements [6]. This paper develops the equations for set theoretic feature-aided tracker. Section 2 formulates the problem. Section 3 describes the mathematics of the set theoretic feature multiresolutional tracking. Results are displayed in Section 4 and Section 5 draws conclusions.

2.0 PROBLEM FORMULATION

Assume that the region in Figure 2, the 2-D frame, is composed of *T* targets with f features. Dynamic target measurements *z*, are taken at time steps *k*, which include target kinematics and 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 a target. The probability density of each measurement feature depends on whether the target is actually present or not. Further assume that a unknown number of kinematic and feature measurements will be taken at each time interval, where we model the clutter composing spurious measurements. A final decision is rendered as to which target feature-set is associated with which [x, y] measurement, determined from the trained feature recognition.

The *multisensor-multitarget tracking problem* is to determine which measured features should be associated with which kinematics in order to optimize the probability that the targets are tracked and identified correctly after z measurements. The multitarget kinematic tracking problem is formulated and solved by using concepts from set-theory probability data association. Since the standard "association rule" - associate the measurement with the highest probability – may lead to ID errors, we utilize a robust set-theoretic approach to capture ID uncertainty. Although it may produce a sub-optimal result when making the final decision, the confidence information associated with the decision, can be used to ensure robustness and capture incomplete knowledge which many trackers lack.

Two methods are chosen. The first, a probability data association (PDA) technique, 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-Set Recognition Tracking*, which is described next, is a procedure that uses position measurements as the coarse local signal for believable target measurements and a precise global feature signal set for discriminating between targets. In the example, we use HRRR amplitudes and locations as the feature set, since closely spaced moving targets require ID for correct measurement-target association [17].

3.0 FEATURE-SET BASED TRACKING

3.1 Tracking

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. *False 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.

A plausible elliptical validation region V, with a *gate threshold*, is set up at every sampling time around the predicted measurement and bounds believable feature-set 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 to discern the correct measurement from the incorrect ones are assumed to be included in the measurement vector. The approaches studied differ in how feature measurements are used in the kinematic-state estimation of the correct target.

3.2 Tracking Belief Filter

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

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 bounds the believable joint measurement 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. 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:

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

ii) and at most one measurement originating from a target:

$$\delta_t(\theta) \overset{\Delta}{=} \mathop{}\limits_{j=1}^{m} \hat{\omega}_{jt}(\theta) \leq 1 \tag{5}$$

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*

$$\tau_j(\theta) \overset{\Delta}{=} \mathop{}\limits_{t=1}^{m} \hat{\omega}_{jt}(\theta) \tag{6}$$

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

The number of *false measurements* in event θ, is

$$\Phi(\theta) = \mathop{}\limits_{tj=1}^{m} [\, 1 - \tau_j(\theta) \,] \tag{7}$$

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

$$P\{\theta(k)|Z^k\} = P\{\theta(k)|Z(k),m(k),Z^{k-1}\} = \frac{1}{c}\, p[Z(k) \mid \theta(k),m(k),Z^{k-1}]\, P\{\theta(k) \mid m(k)\}$$

$$= \frac{1}{c} \prod_{j=1}^{m(k)-\Phi(k)} V\, \{f_{t_t}(k)\, [z_j(k)]\}^{\tau_j} \tag{8}$$

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.

3.3 Set-Based Identification Belief Filter

In *feature-recognition tracking***,** every feature-set measurement in the validation region is evaluated, to determine the expected confidence $C_k(t)$ for assessing the measurement. The training of target features is done to assess a sufficient set of features to identify the target. Although algorithms exist for solving HRRR recognition problems using Bayesian updates, these algorithms employ probability analysis where the most likely target is selected. By employing *belief states,* based on the Dempster-Shafer [18] which incorporate all previous hypotheses, the dynamic-detection trained system is converted to a Markov Decision Problem [19] which augments the measurement association problem to account for incomplete knowledge. Figure 1 shows how kinematic information is used to scramble [2] the incoming features and order them for target recognition.

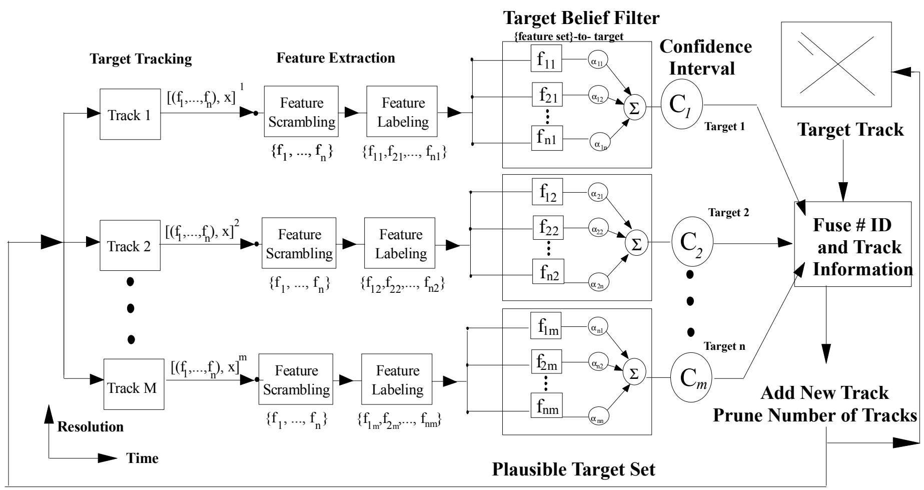

Figure 1. Set Theory HRR Feature Processing.

The belief classification algorithm is based on the statistical behavior of extracted features and is similar to the statistical feature-based (StaF) classifier [20,21,22]. The features, f_{alT}, consist of, *a,* salient peak amplitudes, *l,* feature peak location, and *T* the target profile. Target class hypotheses are defined as the set $\Omega = \{T_1, T_2, ..., T_m\}$ for an algorithm trained on *m* target classes. The location data are represented by $L = \{l_1, l_2, \ldots, l_n\}$ and the peak amplitude data by $A = \{a_1, a_2, ..., a_n\}$ for *n* extracted peaks from an observed target signature. The extracted peak information (shown in Figure 2) from an observation is determined in real-time with priorities, α_{al}, being placed on the salient number of location features. The basic statistical modeling concept is to estimate the probability that a peak occurs in a specific location l_j, given that the observation is from target T_i. Further, the probability that the peak has amplitude a_j, given that the peak is at the location l_j and that the observation is of target T_i, must be determined.

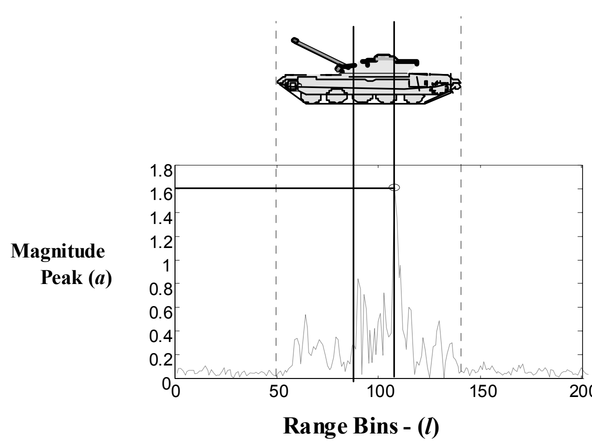

Figure 2. High Range Resolution Profile, showing amplitude(a) and location (l) of range bins.

The primary estimated feature statistics required to determine these probabilities are the peak location probability function (PLPF) and the peak amplitude probability density function (PAPDF); see Mitchell [20] for more details. The role of the *Peak Location Probability Function* (PLPF) estimation is to determine the probability that a peak will be observed in a specific range bin location given that the observation was from some individual target class T_i. This probability is estimated from the peak locations of the training ensemble for each target class. A Parzen estimator with a normal kernel function along the range dimension is employed to estimate the PLPF [20]. With this function, class probabilities are associated with peak locations. However, for robust target classification, additional information is needed from the conditional peak amplitude statistics.

The *Peak Amplitude Probabilities Density Function* (PAPDF) [20] uses amplitude statistics which are conditional on the occurrence of a peak in a specific location and for a given target class. This estimation approach ensures that the amplitude statistics are based only on the detected features rather than a specific range bin location. The form of the amplitude statistical distribution is assumed to be Normal within a given range bin. While it is known that the magnitude of the signatures has a Rician distribution, the Gaussian assumption is reasonable if a "power transform" is performed [20]. The transformation simplifies the problem since the normal PDF is completely specified by two parameters, the mean and variance. These parameters are calculated for each range bin from the amplitudes of the extracted peaks of the training ensemble.

Given the PLPF and peak amplitude PDFs, *class likelihoods and probabilities* are calculated for a set of features. The feature location likelihoods are found by evaluating the PLPF at a specific feature location. The amplitude likelihoods are found in a similar way using a mathematical expression for the Gaussian PDF. The parameters of the Gaussian PDF are the estimated mean and variance terms. The likelihood that the observed feature amplitude is the result of observing target class T_i is found by evaluating

$$p(a_j \mid T_i\, l_i)_\phi = [\, 1 / \sqrt{2\pi\sigma_{ij}}]\ \exp\left[- \frac{(a_j - \mu_{ij})^2}{2\sigma_{ij}^2}\right] \tag{9}$$

where μ_{ij} and σ_{ij} are the conditional mean and standard deviation for peak location l_j given class T_i and target pose angle ϕ. Note that this likelihood is conditioned on both the target class and the feature location. The joint peak location and amplitude likelihood is calculated by multiplying the individual likelihoods,

$$p(l_j\, a_j \mid T_i)_\phi = p(a_j \mid T_i\, l_i)_\phi\ P(l_j \mid T_i)_\phi \tag{10}$$

The *classification 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, $\Theta = \cup\{f_1, .., f_n\}$. Only a subset of the entire combinations of features is possible. Thus, the belief set is a modification of Shafer's belief functions to only include *a priori* trained 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 signature tracking classifications. For individual peak features, class likelihoods, *a posteriori* probabilities, decision confidences from joint likelihoods are calculated. These statistics are used to develop a set of beliefs for specific target hypotheses. The confidences weight the class *a posteriori* probabilities to create a belief in a specific target class. The beliefs are found using:

$$b_k^{T_{hyp}}(T_i \mid a_j\, l_j)_\phi = C^j_{T_{hyp}}(k)\ P(T_i \mid a_j\, l_j)_\phi\ \ \gamma(k), \tag{11}$$

where $C^j_{T_{hyp}}(k)$, is the confidence that the j^th peak is associated with the target hypothesis T_{hyp} for time k and $\gamma(k)$ is a time-discounting effect in evidence accumulation. Since the confidence is based on a class hypothesis, the beliefs generate a matrix [20], which is like a covariance matrix for all plausible targets and an unknown category capturing all unknown targets. Each column of the matrix is associated with a particular class hypothesis. Additionally, an uncertainty value is calculated as $U^{j}_{T_{\mathrm{hyp}}}(k) = 1 - C^{j}_{T_{\mathrm{hyp}}}(k)$ which completes the hypothesis matrix. Note, since the *a posteriori* probabilities sum to unity, the beliefs and uncertainty sum for any given hypothesis is also unity,

$$U^{j}_{T_{\mathrm{hyp}}}(k) + \sum_{\mathrm{i}=1}^{\mathrm{n}} b_{\mathrm{k}}^{T_{\mathrm{hyp}}} (T_{\mathrm{i}} \mid a_{\mathrm{j}}\, l_{\mathrm{j}})_{\phi} = 1. \tag{12}$$

The generation of the beliefs and uncertainties directly ties the confidence that an observed feature is associated with a target hypothesis. Thus, a high uncertainty occurs when the likelihood that the observed feature is not associated with the hypothesized target. By using uncertainty information, unknown target observations are resolved and can be used to determine if the set of targets needs to be increased. Robustness and confidence are obtained through evidential fusion of the individual feature decisions.

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 feature probabilities of track pose and target belief, is obtained by summing over all joint events in which the marginal event of interest occurs. The conditional probability of the event for the continuous kinematic and discrete belief ID [23] is :

$$\begin{aligned}\beta_{jt}(k) &\triangleq \mathrm{P}\{\theta_{jt}(k)|\mathrm{Z}^{k}\} \bullet b_{\mathrm{k}}^{T_{\mathrm{hyp}}} (T_{\mathrm{i}} \mid a_{\mathrm{j}}\, l_{\mathrm{j}})_{\phi} \\ &= \sum_{\theta} \mathrm{P}\{\theta|\mathrm{Z}^{k}\}\, \hat{\omega}_{jt}(\theta) \bullet b_{\mathrm{k}}^{T_{\mathrm{hyp}}} (T_{\mathrm{i}} \mid a_{\mathrm{j}}\, l_{\mathrm{j}})_{\phi} = \sum_{\theta:\theta_{jt}\in\theta} \mathrm{P}\{\theta|\mathrm{Z}^{k}\} \bullet b_{\mathrm{k}}^{T_{\mathrm{hyp}}} (T_{\mathrm{i}} \mid a_{\mathrm{j}}\, l_{\mathrm{j}})_{\phi}\end{aligned} \tag{13}$$

We use the feature measurements for classification and the kinematic measurements for identification as shown below in Figure 3. Since the aperture of the HRR radar is small, we assume that five cluttered sets of range bin features to approximate the radar aperture. Typically, through coherent integration, a HRRR profile is achieved and was presented in Figure 2. Here we relax the constraint such that we have a group of HRRR feature sets and the algorithm must determine the HRRR profile, similar to coherent integration, by scrambling the features and then finding the order the best identifies the target.

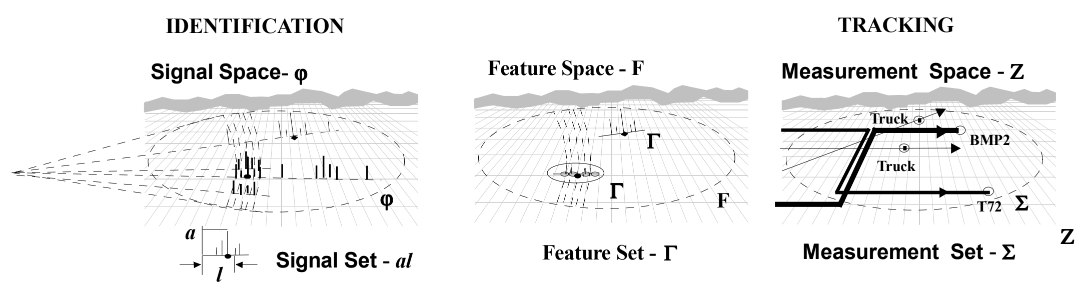

Figure 3. Extracted Feature Sets – Kinematic Σ, Feature Γ, and Signal φ.

To reformulate the classification belief update equation, we assume we have the feature measurements F which are the HRRR amplitude, a, and location, l, measurements being extracted from the set φ. The mass-probability assignment of evidence m, n, for feature set, Γ, and signal set, φ, are:

$$\mathrm{m}_{\Gamma}(\mathrm{F}_{\mathrm{la}}) = \mathrm{p}(\Gamma_{\mathrm{j}} = \mathrm{F}_{\mathrm{la}}) \text{ and } \mathrm{n}_{\varphi}(\mathrm{F}_{\mathrm{la}}) = \mathrm{p}(\varphi_{\mathrm{j}} = \mathrm{F}_{\mathrm{la}})$$

where *al* is the target amplitude and location from the feature identification measurement set *F*. The quantity

$$Bel_{\mathrm{F}_{\mathrm{la}}} = (m{*}n)\,(F_{\mathrm{la}}) \triangleq \frac{1}{1 - L} \sum_{\Gamma \cap \varphi = F_{\mathrm{la}}} m(\Gamma)\, n(\varphi) \tag{14}$$

uses *Dempster's rule of combination*, where $L \triangleq \sum_{\Gamma \cap \varphi = \varnothing} m(\Gamma)\, n(\varphi)$ is called the ***classification conflict*** between the evidence m and evidence n. In this case [1, 24], $Bel_m(F) = p(\Gamma \subseteq F) = \beta_\Gamma(F)$ and $Pl_m(F) = p(\Gamma \cap F \neq 0) = \rho_\Gamma(Z)$ where β_Γ and ρ_Γ are the belief and plausibility measures of Γ, respectively. Likewise, we can construct independent random subsets, Γ, φ, of U (the universal set) such that $m(F_{la}) = p(\Gamma = F_{la})$ and $n(\varphi) = p(\varphi = F_{la})$ for all $F_{la} \subseteq U$. Then, the intersection of the signal and feature set is:

$$Bel_{F_{la}} = (m \oplus n)(F_{la}) = p(\Gamma \cap \varphi \mid \Gamma \cap \varphi \neq 0) \tag{15}$$

for all $F_{la} \subseteq U$. The above equation shows that the *combined belief* in the target location and amplitude measurements *al* of the feature measurement space F, is the probability of intersection of the extracted feature set Γ and the HRR measurement φ. The combined belief of measurement and tracking is:

$$\beta_{jt}(k) \triangleq \sum_{\theta:\theta_{jt} \in \theta} P\{\theta | Z^k\} \bullet [\, Bel^{\phi}_{F_{la}}]^{T_{hyp}}_{k} \tag{16}$$

3.4 State Estimation

The algorithm decomposes the estimation with respect to the origin of each element of the *latest set* of validated feature-set 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:

$$\hat{x}(k|k) = \sum_{i=0}^{m(k)} \hat{x}_i(k|k)\, \beta_i(k) \tag{17}$$

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:

$$\hat{x}_i(k|k) = \hat{x}_i(k|k-1) + W(k)\nu_i(k) \tag{18}$$

$$\nu_i(k) = z_i(k) - \hat{z}(k|k-1) \tag{19}$$

$$W(k) = P(k|k-1)H(k)^T S(k)^{-1} \tag{20}$$

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

$$\hat{x}(k|k) = \hat{x}(k|k-1) + W(k)\nu(k) \tag{21}$$

$$\nu(k) = \sum_{i=1}^{m(k)} \beta_i(k)\, \nu_i(k) \tag{22}$$

$$P(k|k) = \beta_o(k)P(k|k-1) + [1-\beta_o(k)]P^c(k|k) \tag{23}$$

where the covariance of the state is updated with the *correct measurement* is:

$$P^c(k|k) = P(k|k-1) - W(k)S(k)W(k)^T \tag{24}$$

Note that belief functions, based on a set theoretical approach, modify the combined innovation matrix. Thus, by capturing incomplete knowledge in target identification, the belief set approach does not overestimate the probability associated with exact modeling. Furthermore, the belief approach adds robustness to target tracking. The *prediction* of the state and measurement to time k+1 is done as in standard filtering.

4.0 Results

The two dynamic tracking methods discussed are compared. The method for evaluating performance is a Monte Carlo simulation and the performance metric is normalized probability of state error. It is assumed that the features in question are the HRRR profiles from the Moving and Stationary Target Acquisition and Recognition data set. Specifically, the T72 and BMP2 were used in the simulation and clutter consisted of nine other targets. As detailed in the Figures 4 and 5, by the true trajectory, the targets 1) start with position X = {(2000,1200), (2000,9800)} and speeds of +10 x *m/s*, 2) pass by each other at a distance of 5 meters and speeds of -2 and + 2 y *m/s*, and 3) finish with a speed of +10 x *m/s*.

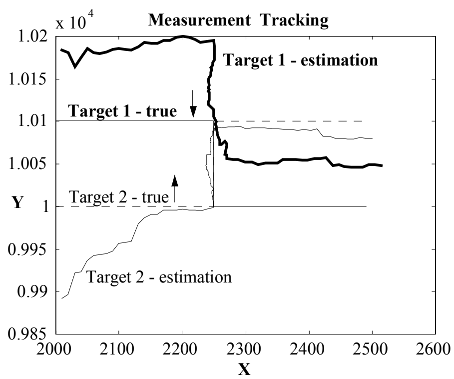

Figure 4. Measurement Tracking

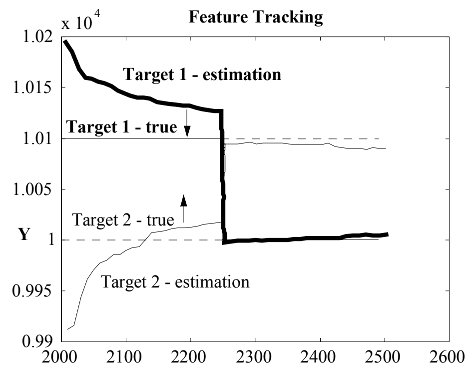

Figure 5. Set-theory Feature Tracking

Table 1: Normalized Square Errors

State Error	X1	X2	Y1	Y2
Measurement	101.84	98.45	6.63	3.50
Feature Recognition	48.39	47.59	2.20	1.21

5.0 Discussion & Conclusions

The figures above show that measurement tracking incorrectly associates some of the measurement data from the second target with that of the first target. The set theoretic feature-identification tracking algorithm, which uses a amplitude and range-bin features with measurement and target uncertainty, detects the HRRR profile of each target and correctly assigns measurements to the targets. Information is updated by the feature information for feature-level fusion. It is noted that the discrimination of the targets was cluttered with HRRR profiles near the pose angle of the target. The belief filter was able to propagate features to discern the correct order of the following target features.

The presented set-theoretic feature track and identification technique demonstrates promise for multitarget tracking problems and warrants further exploration in problems where environmental effects, occlusions, and lost sensor data can be modeled that are not readily handled by current tracking algorithms. Further efforts include enhancing the set space to assess confidence values for military-application viability and operational readiness verification.

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