Ten Methods to Fuse GMTI and HRRR Measurements For Joint Tracking and Identification

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Abstract – *Mutual-aided target tracking and identification (ID) schemes are described by exploiting the couplings between the target tracking and object ID systems, which are typically implemented separately. A hybrid state space approach is formulated to deal with continuous-valued kinematics, discrete-valued target type, and discrete-valued target pose (inherently continuous but quantized). We identify ten possible mutual aiding mechanisms with different complexity in different levels. The coupled tracker design is illustrated within the context of using ground moving target indicator (GMTI) and high-range resolution radar (HRRR) measurements as well as digital terrain elevation data (DTED) and road maps. The resulting coupled tracking and ID system is expected to outperform the separately designed systems particularly during target maneuvers, for recovering from temporary data dropout, and in a dense target environment. We simulate HRRR ID support information to assist in pose-model selection of an Interacting Multiple Model (IMM) tracker using GMTI measurements.*

Keywords: Fusion, Tracking, Identification, Pose, IMM.

1. Introduction

Radar tracking algorithms typically model a target of interest as a point source in space (i.e., an equivalent RCS center). The algorithms utilize ranging measurements (range, range rate, elevation and azimuth of the line of sight (LOS) from radar to target) to estimate the target kinematic state (position, velocity, and/or acceleration) by a tracking Kalman filter.

High-range resolution radar (HRRR), on the other hand, attempts to extract a target range profile and to compare it with known profile templates for matching, thus achieving target type classification. Range profile is one-dimensional measurement of target radar reflectivity along the radar to target LOS, thus being a function of the LOS angles. This look vector can also be expressed in terms of the aspect (or articulation) and depression angles in the target body frame, called a "pose," as illustrated in Figure 1. For practical reasons, a target is typically pre-sampled into a template library in its range profile at discrete poses. A successful template matching therefore classifies the target type and at the same time produces the pose at which the

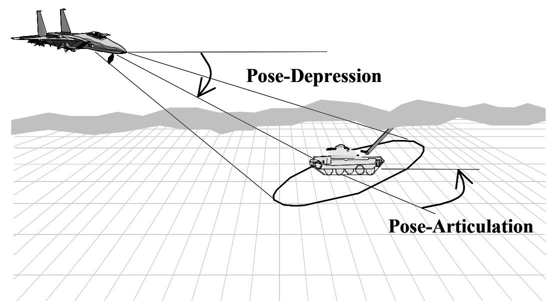

Figure 1. Pose Angle Defined in Terms of Aspect (Articulation) and Depression Angles

range profile is viewed. Figure 2 shows a high-resolution range profile.

It has been recognized [1] that couplings between tracking and classification systems via pose, kinematic, and association constraints can be exploited to improve performance such as determining the target ID (note: ID distinguishes between targets of the same class). However, most target tracking and classification systems are implemented independently. This has both theoretical and practical reasons. One practical limitation in the past was the lack of sensor accuracy/resolution and powerful computers for reliable implementation in real time. When target tracking and ID are considered jointly, we deal with a hybrid space. That is, the target state vector and its

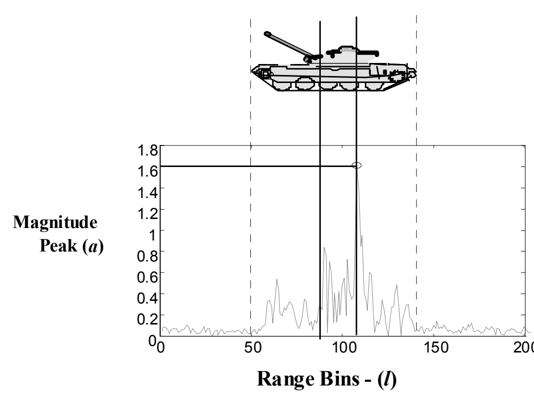

Figure 2. High Resolution Range Profile (amplitudes are statistical features).

measurements in target tracking systems are continuous-valued (real numbers) whereas the target type is discrete-valued and so is the target pose due to quantization. The relationships between a target state vector and its measurements are well understood analytically. However, it is difficult to establish analytic models between a target type and its range profiles for all possible poses (except for two-dimensional look-up table interpolation from a template library). Furthermore, there are no adequate dynamic models (except probabilistic) relating the continuous kinematic state and the discrete pose and their respective measurements for a moving target, which may undertake maneuvers.

One approach to solving the technical challenges while meeting the application needs is to explicitly exploit the couplings between tracking and ID systems. [2] In this paper, we will utilize ground moving target indicator (GTMI) and HRRR measurements as well as digital terrain elevation data (DTED) and road map as a case study to examine all possible couplings between the target tracking and target identification systems. We identify those couplings that have a high potential to improve the overall system performance and develop necessary mathematical methods to characterize the couplings for mutual aiding.

2. Tracking and ID Couplings

In this paper, we will focus on typical air-to-ground scenarios where the tracking and ID sensors will be limited to GMTI and HRRR with DTED and road maps. Other advanced sensor modes such as ISAR and MTIm can also be added. Couplings between target tracking and ID with GTMI and HRRR measurements can take place in three levels, namely, measurement, filtering, and utilization, with the following list of ten possible couplings as visualized in Figure 3. The list is meant to overview methods and points the reader to references for more information. Space limits a full delineation.

1. Type for data association [A]. [1,3,4] Target type information can be used to improve the process of associating radar returns with correct target tracks particularly when closely spaced or crossing targets are encountered. It is equally helpful when the target disappears and then reappears due to obscuration or after it slows down below the minimum detectable velocity (MDV) for a sharp turn.

2. Type as kinematic constraints [B]. [1,2] For a particular type of targets, its possible range of maneuvers (maximum speed, acceleration, turn rate, off-road capability, etc.) can be used to select the most appropriate set of models for the tracking filter and to reinforce this particular type of target models by increasing its contribution (probabilistic weighting) toward the final state estimate.

3. Pose-derived acceleration [C]. Ground vehicles such as tanks tend to move at constant speeds, maneuvering by turning sharply at "random" times. The resulting trajectory resembles a collection of connected arcs separated by occasional tangential line segments [5]. The centripetal acceleration can be determined from the vehicle speed and the rate of change of orientation during acceleration. In a hostile environment, the constant speed will be close to the maximum value as allowed by the vehicle design and the terrain. If the consecutive pose readings from the target identification system allow us to estimate the rate of change of orientation, the target acceleration can be derived as an input to the tracking system [6, 7]. For an airborne target such as helicopter and aircraft, the link between the body attitude and acceleration has been proposed for tracking improvement [8, 9].

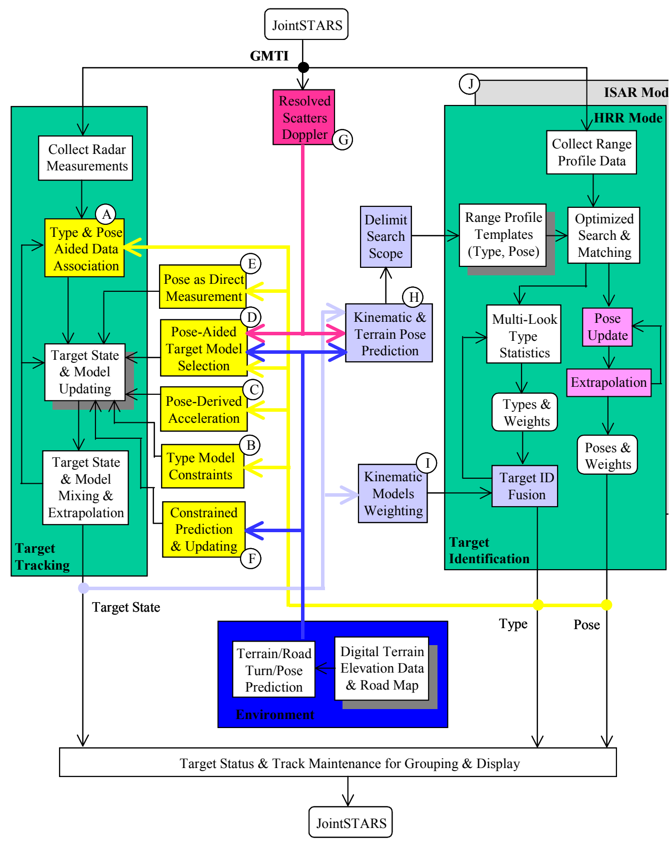

Figure 3. Tracking and ID couplings.

4. Pose as a filter model selector [D]. If the above pose-derived acceleration estimate in an IMM [2] is difficult or not practical due to complexity or lack of accuracy, an alternative approach is to obtain from the sequence of pose changes a set of probabilistic weightings on the multiple models used by the tracking filter.

5. Pose as a derived measurement [E]. [1,2]. For ground vehicles, their velocity vector is mostly aligned with the body longitudinal axis. As a result, the pose estimate can be used as a derived measurement of the direction of the target velocity vector.

6. Terrain/road-constrained kinematic updating [F]. [2,10] The width of a road when read from a digital map can be used as position constraints for updating and prediction. For an on-road vehicle, the curvature of a road ahead provides an early indication of turn maneuver and its turning radius, which can be used to increase the likelihood of the turn model of the tracking filter.

7. Resolved scatter Doppler for estimating body motion [G]. If the Doppler associated with individual scatterers on a target can be resolved, it can provide measurements to estimate body motions. Such a motion estimate can be used to track pose and particularly sharp turns at stop or at a speed below MDV. The detected rotation of major scatterers can be used at least to weigh in favor of the turn maneuver model in the tracking filter.

8. Kinematics and terrain/road data for narrowing search space [H]. .A vehicle attitude and its rate of change can be determined from its velocity vector and the local terrain gradient. In addition, for ground vehicles, their heading (velocity vector) is mostly aligned with the body centerline (no sideslip angle). As a result, an accurate estimate of the velocity vector (i.e., body longitudinal direction) and its estimation error covariance can be converted into a pose estimate and its confidence interval. Together, they can be used as the reduced search space for pose estimation and type identification.

9. Kinematics to assist target identification [I]. The kinematic estimates for each target type under consideration can be used to differentiate one from another. This can be done at least in two ways. One is to fuse the probability of each type being true as derived by the tracking filter with the statistical measure of each type based upon matching between the current range profile measurement and all type templates. The other way is to exclude certain types of targets based upon the observed dynamic behavior and trajectory pattern, which they are incapable of by design.

10. Call for better imaging sensors [J]. The GMTI tracking filter may issue requests for additional resource such as ISAR and MTIm modes for better target identification or more accurate pose estimation to help HRRR at critical moments. It is important to know the limits of each sensor and know when to make the call.

Target type and kinematic state may be considered jointly for group tracking [10] and for determining other tactical information such as who comes from where (source) and heads toward where (sink) using which route (line of communication). Among the list of possible couplings between the target tracking and target ID systems described above, we concentrate below on the filtering aspect in greater details in the next section.

3. Feature-Aided Tracking

In this section, we look into those coupling mechanisms that are relatively simple and of high potential, by which target tracking algorithms can be aided with pose estimates. Target feature integration (e.g. shape, signal) allows for measurement verification as well as robust target pose (position and orientation) estimation.

For fixed wing or rotary wing aircraft, the orientation is directly related to target acceleration (direction and amplitude). This relationship has been proposed to enhance aircraft tracking with imaging sensors [11,12,13]. However, there is no such a connection for tracked or wheeled vehicles for they stay level on the terrain surface while turning. A single view of a turning vehicle looks the same as it going straight because almost no sensor can see the turning wheels. Nevertheless, ground vehicles roll over terrain surface, causing the velocity vector to be in the direction that the vehicle is pointed except for small sideslip angles. Multiple views of the same target, however, can reveal if it is turning and if so, how fast.

Three methods (C, D, and E) as shown in Figure 3 exploit such couplings. Their performance will vary as a function of the pose estimate accuracy under different operating conditions such as at stop, in steady motion, and making turns.

3.1 Method E: Pose as a derived measurement

In the early work [1,2], the pose estimate corresponding to the maximum range profile matching for a given target type is used as a derived measurement to the associated tracking Kalman filter. By the assumption that the ground vehicle velocity vector is mostly aligned with its body principal axis, this pose estimate when transformed to the body frame or a common reference frame provides a measurement of the vehicle heading or the direction of the velocity vector.

When the range profile template has a very fine resolution, that the template matching finds the right pose, and that the sideslip angle is small, this pose estimate can provide an accurate and fast updating of the Kalman state. This is because a pose estimate bears more information than a range or range rate. The latter as a scalar is the projection of the velocity vector onto the LOS vector, thus less informative than the vector direction itself.

However, when the above conditions do not hold, the pose estimate may be poor or even erroneous. If still used as a direct measurement, it would adversely affect the tracking performance. Other methods can be used instead.

3.2 Method C: Pose-derived acceleration

This approach attempts to estimate target acceleration and thus can be very effective during target maneuvers. To implement this approach, the linear acceleration is estimated from a sequence of poses by determining its turning rate. To drive the turning rate from poses, consecutive multiple looks are required and the target pose is tracked as an independent state. At a first glance, this is a simple two-state (pose and pose rate) process. In reality, however, it is much more complicated. First, to an observer, the unknown pose is a random variable subject to large changes at random due to maneuvers. More importantly, the observed pose from a target identification system such as 1D HRR matching is artificially made discrete due to angular quantization and since the recognition/matching process is not perfect, the pose value may be erroneous.

We actually encounter a problem of estimating the underlying maneuver from a sequence of discrete-time discrete-valued pose observations (a point process). The underlying maneuver is estimated from the sojourn time in each pose and the transition from one pose to another, rather than the individual poses. As a result, the pose accuracy is less an issue (a limiting factor) in this formulation than Method E described above.

The hybrid estimation theory based on continuous-time stochastic differential equations [14] may be applied to this problem. However, since no closed-form solution is available for the continuous-time filter, its implementation would require real-time integration of differential equations (high-order integration schemes with variable integration steps may be required to ensure good numerical behavior). In contrast, a discrete-time formulation may be easier from an implementation point of view. The discrete-time mode filters for point processes have been derived [15,16] and applied to maneuvering target tracking with an imaging sensor [7], which can be used to model the pose measurement of HRRR and its dynamics.

Due to the inherent randomness, measurement noise, and quantization errors, the pose dynamics is suitably characterized by a probabilistic transition matrix, with the transition probability from one pose to another as the inverse sojourn time in the pose proportional to the underlying maneuver. The sequence of pose measurements is modeled with a confusion matrix. The resulting mode filter [15,16] provides an estimate of the unknown acceleration (or turning rate) as well as its estimation error covariance. In this way, not only the orientation-derived acceleration but also its estimation error covariance can be incorporated into a second-order extended Kalman filter (EKF) to ensure performance robustness. [7]

3.3 Method D: Pose-aided target selection

The interacting multiple model (IMM) estimator [17] is popularly used to describe the target kinematics with different maneuvers. The IMM algorithm delivers its final estimate and covariance as the weighted sums of all model filter estimates and their respective covariance matrices. The weights used in the summation are the probability for the corresponding model being true.

In most implementations, however, the IMM algorithm determines its model weights solely based on the residuals of its measurements under the general Gaussian noise assumption. As such, it does not use any external "support" information except for the a priori probability for each model as being true at the very beginning.

With HRRR available, each time the target identification system processes a range profile measurement, the mode filter will produce the type and pose estimates as well as their probabilities as being true. By consequence, in addition to using this pose estimate as an extra measurement to the tracking filter (Method E) or deriving an acceleration estimate from it (Method C), we may simply generate a probabilistic support for a particular kinematic model in the tracking filter.

The pose-derived model weights can then be combined or fused with the kinematic-based model probabilities using either the point-process filtering or by a Bayesian inference method or with a belief classification filter. This external supported IMM algorithm, though being not as fast as Method E or C in responding to a maneuver, is definitely simpler and may be more robust in cases where pose estimates are poor.

4. Kinematics/Terrain-Aided Target ID/Pose Estimation

Target kinematics and terrain/road data can be used to improve target ID and pose estimation. Three techniques are described below. The first two techniques attempt to reduce the type and pose search space over which the range profile templates will be searched for matching (Method H of Figure 3) whereas the third technique is to fuse type decisions made from GMTI and HRRR measurements (Method I).

One technique to aid target ID is to reduce the set of possible types for a target under surveillance based on the kinematic estimate and observed trajectory pattern in comparison to the design capability of each type, the terrain conditions, and the tactical environment. [1] This may exclude certain types from being further considered in the tracking filter.

A more direct technique is to obtain a reliable interval for possible target poses prior to the search in range profile for a given target type. [1] Target position and velocity estimates and their standard deviations can be used for this purpose. When DTED data is available, a vehicle's attitude can be estimated from the gradient at its location given the heading (i.e., along the velocity vector). If the vehicle is on road, the road direction can be used as a first estimate of its heading. However, the accuracy of such an attitude estimate depends on the digital terrain grid resolution and its accuracy, the position and velocity errors, and a possible sideslip angle.

In addition to aiding target pose estimation, the DTED and road map can also be used to improve kinematic state estimation. [10] With the vehicle velocity known, the change rate in attitude is determined by the terrain gradient. Similarly, the curvature of a road can be used to predict the imminent turn maneuver as well as turning radius given the speed. The local slope of the terrain is likely to influence the vehicle acceleration, e.g., slow down going uphill while speed-up downhill. These quantities can be incorporated into target tracking algorithms as extra measurements and/or model weighting factors. Moreover, the road width can also be used as constraints to delimit the position estimate and its prediction for better road following.

Many databases of range profile templates and techniques of detection and classification have been developed and reported in the literature. [1,4,18] To improve their target classification in terms of search speed and successful rate of identification, a third technique is to fuse the probability for each type being true derived from the tracking filter's kinematics with the statistical measure of each type based upon matching between the current range profile measurement and all types in the template library. This is the complementary operation of Method D as described in Section 3.3.

5. Hybrid Modeling For Filter Design

In this section, we present the modeling of discrete-valued pose dynamics, its measurement process as well as estimation.

The kinematic state (i.e., position, velocity, and/or acceleration) of a target when viewed by a tracking radar with ranging measurements (i.e., range, range rate, elevation and azimuth) is continuous-valued (or real-valued). On the other hand, an HRRR provides 1D range profiles of a target (i.e., the target radar reflectivity along the radar to target LOS direction). Since each target's template library only contains its range profiles sampled at discrete poses (i.e., the aspect and depression angles in the target body frame), template matching therefore provides a quantized pose reading, which thus becomes discrete-valued. Given a range profile measurement, its correlation with the entire template library typically does not provide a single decisive matching at a discrete pose for a particular type but rather a distribution of correlation values over a range of possible poses for different target types. This is due in part to cross-correlation between range profiles at adjacent poses (or some features extracted from the range profiles), thus defining the angular resolution of pose estimation as well as the inherent discernibility (or lack of discernibility) for a target type and between target types.

Three models of the pose measurement process and their associated estimation filters are presented below. Due to quantization, the underlying pose of a target in a particular type, denoted by *p(t)*, takes a value from a discrete set:

$$p(t) \in P = \{p_1, p_2, .., p_M\} \tag{1}$$

Introduce an indicator vector $\rho(t)$ for the discrete variable p(t) such that the ith element of $\rho(t)$ is:

$$\rho_i(t) = \begin{cases} 1 & p(t) = p_i \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

5.1 Modeling As Discrete-Time Point Process

In the first model, a decision is made by picking the type and pose corresponding to the largest correlation peak. The output of this measurement process is denoted by $n_i(t) = 1$ when a pose estimate of $p(t) = p_1$ is declared for i = 1, …, M. The HRRR matching outcome is thus mapped into an indicator vector $n(t) = [n_1(t), .., n_M(t)]^T$.

The process of range profile measurement, matching, and classification is not perfect. The HRRR matching outcome $n_i(t)$ is not always equal to $\rho_i(t)$ and this discrepancy can be characterized by the discernibility matrix $D^k = [\, d^k_{ij} \,]$ as:

$$d^k_{ij} = P\{n_j(t) = 1 \mid \rho_i(t) = 1, \phi_k(t) = 1\}$$

$$\text{with} \quad \sum_{j=1}^{M} d^k_{ij} = 1 \tag{3}$$

where $\phi_k(t)$ is the kth element of $\phi(t)$, which is the underlying dynamics state vector of the discrete-valued pose. This is also the arrival rate of $n_j(t)$ at time t when $\rho_i(t) = 1$ for a given maneuver $\phi_k(t) = 1$ (when $n_k(t)$ is viewed as a point process).

After the radar platform's motion is compensated for from the HRRR measurements, the changes of pose over time reflect the target dynamics. For a ground vehicle target, it is reasonable to describe the pose transition under maneuver (acceleration upon velocity) in a probabilistic setting. For the maneuver kinematic analysis, we use a constant velocity and constant acceleration white noise models and a Markov acceleration process model. [2]

Assume that any maneuver will take one of N possible acceleration vectors $a(t) \in A = \{a_1, a_2, …, a_N\}$ or equivalently $a(t) = A\phi(t)$ with $\phi(t)$ being the indicator vector of a(t), similarly defined as in Eq. (2). Since the maneuvering strategy is almost unknown, the random change of acceleration may be modeled as a homogenous Markov chain, specified by its transition probability matrix $\Pi^{\phi} = [\, \pi^{\phi}_{ij} \,]$ as:

$$\pi^{\phi}_{ij} = P\{a(t+1) = a_j \mid a(t) = a_i\} = P\{\phi_j(t+1) = 1 \mid \phi_i(t) = 1\}$$

$$\text{with} \quad \sum_{j=1}^{N} \pi^{\phi}_{ij} = 1 \tag{4}$$

Under a particular maneuver, the pose dynamics is also assumed to be a Markov process and described by the matrix of transition probabilities $\Pi^{\rho}_k = [\, \pi^{\rho}_{kij} \,]$ with:

$$\pi^{\rho}_{kij} = P\{p(t+1) = p_j \mid p(t) = p_i, a(t) = a_k\}$$
$$= P\{\rho_j(t+1) = 1 \mid \rho_i(t) = 1, \phi_k(t+1) = 1\}$$

$$\text{with} \quad \sum_{j=1}^{M} \pi^{\rho}_{kij} = 1, \; k=1,2,\ldots,N \tag{5}$$

where each transition probability can be chosen to match the mean transition time from one pose to another under the maneuver.

This model indicates that the dynamics state $\phi(t)$ is related to the range profile matching outcome $n(t)$ via the pose variable $\rho(t)$. As a result, $\phi(t)$ and $\rho(t)$ are two "hidden" processes and their combination affects the range profile measurements over time. Define the composite state of $\phi(t)$ and $\rho(t)$ as:

$$\xi = [\phi_1\rho_1, ., \phi_1\rho_M, ., \phi_N\rho_1, ., \phi_N\rho_M]^T = \phi(t) \otimes \rho(t) \tag{6}$$

where is the Kronecker product. The original processes can be reconstructed from $\xi(t)$ as:

$$\phi(t) = [\, I_{N\times N} \otimes 1^T_M \,] \quad and \quad \rho(t) = [1^T_N \otimes I_{M\times M}] \tag{7}$$

where $I_{N\times N}$ stands for an N by N identity matrix and 1_N indicates an N-vector with all ones, respectively.

It is easy to verify that $\xi(t)$ is also a Markov process with the transition probability matrix $\Pi^{\xi} = [\pi^{\xi}_{mn}]$ calculated from Π^{ϕ} and Π^{ρ}_k as:

$$\pi^{\xi}_{mn} = P\{\xi_n(t+1) = 1 \mid \xi_m(t) = 1\}$$
$$= P\{\phi_k(t+1) = 1, \rho_j(t+1) = 1 \mid \phi_\ell(t) = 1, \rho_i(t) = 1\}$$
$$= \pi^{\rho}_{ijk}\; \pi^{\phi}_{\ell k} \tag{8}$$

where the indices of (i, j) of $\rho(t)$ and (l, k) of $\phi(t)$ define m and n in $\xi t)$, respectively.

A matrix form of the arrival rate for $n(t)$ as related to the composite state variable $\xi(t)$ can now be written for the HRRR measurement process as:

$$\Lambda = \begin{bmatrix} d^1_{11} & \ldots & d^1_{M1} & \ldots & d^N_{11} & \ldots & d^N_{M1} \\ & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ d^1_{1M} & \ldots & d^1_{MM} & \ldots & d^N_{1M} & \ldots & d^N_{MM} \end{bmatrix} \tag{9}$$

The estimate of the composite state $\xi(t)$ in the mean square sense given the current and past pose measurements denoted by $N_t = \{n(s), s \le t\}$ is written as:

$$\hat{\xi}(t \mid t) = E\{\xi(t) \mid N_t\} \tag{10}$$

which as the conditional expectation affords a natural interpretation that its i^{th} component is the a posteriori probability of $\xi_k(t) = 1$ (i.e., the i^{th} state is true) given N_t.

With the above models, the mode filter [7,15,16] for discrete-time point process can be applied to estimate the composite state and its estimation error covariance matrix.

5.2. Bayesian Modeling

Instead of making a "hard" decision as to which pose and type for each range profile measurement, the second model generates a vector of likelihood functions for all possible poses and types according to the correlation between the range profile measurement and all items in the template library. The correlation values can be normalized to indicate their respective "likelihood" to be true given the measurement. Those values that are below a certain threshold can be excluded from further consideration, thus reducing the problem dimensionality. Alternatively, a Gaussian density function can be assigned to each correlation when the noise terms in all range bins are assumed to be independent. Since correlation is a linear operation, the resulting correlation noise is Gaussian distributed according to the central limit theorem.

A range profile measurement at time t is denoted by $z(t)$. Its correlation with the reference range profile sampled at pose $p(t) = p_i$ in the template library is denoted by $c_i(t)$. The resulting likelihood function for pose i under dynamic state k is denoted by $g_k[c_i(t)]$ for $i = 1, \ldots, M$ and $k = 1, \ldots, N$. Put individual likelihood functions into a vector:

$$L[z(t)]=[g_1[c_1(t)],.,g_1[c_M(t)],.,g_N[c_1(t)],.,g_N[c_M(t)]]^T \tag{11}$$

Define the composite state estimate as the conditional expectation (i.e., the a posteriori probability) as in Eq. (9). Then applying the Bayes' formula, a recursive algorithm to calculate the composite state estimate is obtained with

$$\hat{\xi}(t \mid t) = \frac{diag\{L[z(t)]\}\hat{\xi}(t \mid t-1)}{L[z(t)]'\hat{\xi}(t \mid t-1)} \tag{12}$$

being the measurement updating equation;

$$\hat{\xi}(t \mid t-1) = (\Pi^{\xi})'\hat{\xi}(t-1 \mid t-1) \tag{13}$$

being the one step ahead prediction equation, and $\hat{\xi}(0 \mid 0) = \hat{\xi}_0$ being the initial condition.

The estimates of $\rho(t)$ and $\phi(t)$ and their respective covariance matrices can be recovered from the composite state estimate $\hat{\xi}(t \mid t)$ and $cov[\hat{\xi}(t \mid t)]$, which can be used in turn in the tracking filter via Method C, D, or E described in Section 3.

5.3 Modeling with Confidence Belief Measure

A belief classification filter can be constructed based on statistical features of an observed object in HRRR returns. As shown in Figure 2, a possible set of such features consist of s-extracted salient peak amplitudes $A = [a_1, a_2,$

..., a_s] at the respective peak locations $L = [l_1, l_2, ..., l_s]$ for each pose $p \in P = \{p_1, p_2, ..., p_M\}$ of a given target type. A statistical approach will first estimate the probability that a peak occurs in a specific location l_q given that the observation is from the target of interest at pose p_r, denoted by $p\{l_q|p_r\}$ and the probability that the peak has amplitude a_q given that the peak is at the location l_q for the target at pose p_r, denoted by $p\{a_q| l_q, p_r\}$. The joint peak location and peak amplitude likelihood given the target pose is calculated as the product of the individual likelihoods:

$$p\{a_q, l_q| p_r\} = p\{a_q | l_q, p_r\}\, p\{l_q|p_r\} \tag{14}$$

The a posteriori probability for the pose is calculated using the Bayes' rule as:

$$P\{p_r \mid a_q, l_q\} = \frac{p\{a_q, l_q \mid p_r\} P\{p_r\}}{\sum_{u=1}^{M} p\{a_q, l_q \mid p_u\} P\{p_u\}} \tag{15}$$

The above equations are similar to those given in Eqs. (11)-(13). As pointed out in [1], however, this Bayesian calculation only provides a relative probabilistic information contained within and with respect to the set of original hypotheses, rather than global information. As a result, the Bayes' rule alone will not be able to reject incorrect decisions due to unknwon object or statistics. Since the information required to eliminate those errors can be derived from the likihood values, it becomes evident to incorporate the likelihood information into the decision process in the form of a belief measure with an associated belief-probabilistic uncertainty.

The decision confidence measure can be based on the hypothesis likelihoods using their probability density functions developed for each hypothesis. Larger likelihood decisions should have a higher confidence. The cumulative distribution function (CDF) mirrors this concept and can thus be used to determine the decision confidence. The confidence that the observed peak a_q is associated with the given target at pose p_r at the event time k is defined as:

$$C^r_{Hyp}(k) = F\{ p\{a_q, l_q| p_r\} \leq x\} \tag{16}$$

where the subscript indicates the confidence measure is for a known hypothesis, x is a likelihood value, and $0 \leq F\{\bullet\} \leq 1$ stands for the CDF. The corresponding uncertainty value is defined as $U^r_{Hyp}(k) = 1 - C^r_{Hyp}(k)$. The beliefs are found using:

$$Bel_k^{Hyp}(p_r \mid a_q, l_q) = C^r_{Hyp}(k) P(p_r \mid a_q, l_q) \tag{17a}$$

$$U^r_{Hyp}(k) + \sum_{i=1}^{M} Bel_k^{Hyp}(p_i \mid a_q, l_q) = 1 \tag{17b}$$

Put the beliefs for individual pose hypotheses into a vector as $\underline{Bel}_k = [Bel_k^1, \ldots, Bel_k^M, Bel_k^{Unk}]^{\mathrm{T}}$, where "Unk" represents what is beyond the known hypitheses (i.e., an unknown pose value not sampled for the template library in our case). The dimesnion is thus increased from M to $M+1$. Dnoting the probabilistic transition matrix by Π, we can then write the propagation of the beliefs over time as:

$$\underline{Bel}_{k+1} = \Pi\, \underline{Bel}_k + \underline{U}_k \tag{17c}$$

where $\underline{U}_k = [U_k^1, \ldots, U_k^M, U_k^{Unk}]'$ is the uncertainty, typically modeled as a zero-mean Gaussian process with a known covariance matrix.

The above updating and propagation equations of the belief classification filter can be formulated in conjuntion with the underlying acceleration (i.e., the composite pose and acceleration state). In this way, it yields a joint target tarcking and ID system in terms of the belief probabilistic state and measurement equations and its filter [1].

6. Simulation Results

In this section, we present simulation results assessing the benefits of mutual aided target tracking and ID. Of special interest is to evaluate the benefits of correcting the maneuver model hypotheses with an external information support (Method D: Pose as a model selector for an IMM). To do this, a stand-alone maneuvering target tracking IMM estimator is used with positional measurements only to set up the performance benchmark. Right after the maneuver, we apply the HRRR-derived external support information [1, 18] to assist the IMM estimator. The performance improvement in terms of RMS errors (of position and velocity) is assessed as a function of how early and how well the external source weighting is provided as compared to the benchmark. This information can also be used as design requirement, which a pose estimation algorithm needs to meet in order to benefit from the GMTI and HRRR interaction.

The measurement error standard deviations used in the filter are twice those used in the truth data generation (the filter is pessimistic about its measurements). Figure 4 shows the model probabilities when the accelerations used in Model 1 and Model 2 are half of the true values. The three models are made closer than the actual data. It is thus less sure during the quiescent without maneuver. Figure 5 shows the model probabilities when the accelerations used in Model 1 and Model 2 are double of the true values. It has good model separation during the non-maneuver period but is less sure about the maneuvers because its models are larger than the actual data. The RMS values are in Table 1.

Table 1. Position and Velocity Estimation Errors Statistics

STD	(A_x, A_y)	rms-X	rms-Y	rms-V_X	rms-V_Y
$\sigma_{x,y} = 50$m	$\div 2$	12.9613	19.4996	0.2124	0.3881
$\sigma_{\psi} = 1^{o}$	$\times 2$	11.9094	52.7609	0.2463	1.1802

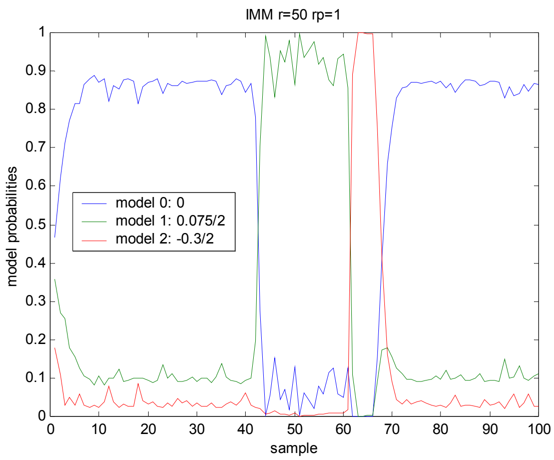

Figure 4. IMM track and ID with acceleration models (acceleration = half true values).

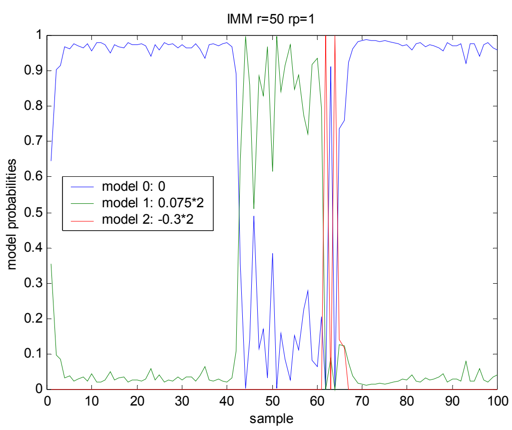

Figure 5. IMM track and ID with acceleration models (acceleration = double true values).

7. Summary

In this paper, we first described ten possible couplings between target tracking and target identification systems for mutual aiding to enhance their respective performance. We then outlined three specific techniques for making use of target pose information to aid target tracking on the one hand and also three specific techniques to use target kinematics and DTED as well as road map to aid target pose estimation on the other hand. A hybrid state space modeling was presented to characterize the continuous-valued kinematics, discrete-valued target type, and discrete-valued target pose (inherently continuous but quantized). These models are indispensable for mutually aided tracking filter design. A pose-derived acceleration model selection was highlighted in this paper using HRRR support identification measurements. Future reports will demonstrate results of each method presented.

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