E. Blasch, "Modeling Intent for a target tracking and identification Scenario," *Proc. SPIE*, Vol. 5428, April 2004.

Modeling Intent for a Target Tracking and Identification Scenario

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ABSTRACT

The tracking goal is to reduce positional uncertainty. There are many ways to reduce tracking uncertainty: including classification data, using trafficability maps, and employing behavior information. We seek to extend tracking and identification modeling by incorporating intent to update prediction velocity vectors. A hybrid state space approach is formulated to deal with continuous-valued kinematics and discrete-valued target type, pose (inherently continuous but quantized), and intent behavior. The coupled tracker design is illustrated within the context of using ground moving target indicator (GMTI) and high range-resolution (HRRR) measurements as well as digital terrain elevation data (DTED), road map, and estimated goal states. The resulting Intent Coupled Tracking and Identification (ICTI) system is expected to outperform separately designed systems particularly during target maneuvers and recovering from temporary data dropout.

Keywords: Intent, Fusion, Tracking, ID, User Refinement, Pose Estimation, IMM, Terrain, DTED, and Road

1. INTRODUCTION

The standard user fusion model incorporates many modeling constructs for analysis such as level 1 object tracking and identification, level 2 situation assessment, level 3 impact assessment, and level 5 user refinement, as shown in Figure 1. [5, 7] An intersection of these different fusion processes is **target intent**. Intent is the purpose of meaning of action. For an object being tracked, the target behavior can convey intent information, such as a target moving rapidly might imply fleeing from a location. In order to design accurate trackers, we are interested in modeling the possible target intent so as to reduce the positional error. As a preliminary investigation in intent tracking, we utilize a variable-state interacting multiple model (VS-IMM) tracker with kinematic, classification, in intent models for the Intent Coupled Tracking and Identification (ICTI) system. Other feature-aided tracking approaches include the wavelet [14], hypothesis and classification, [10] and vision [17]. Variants of the IMM [9] include the IMM-fuzzy [12], IMM-JBPDAF [6], and MS-IMM [23].

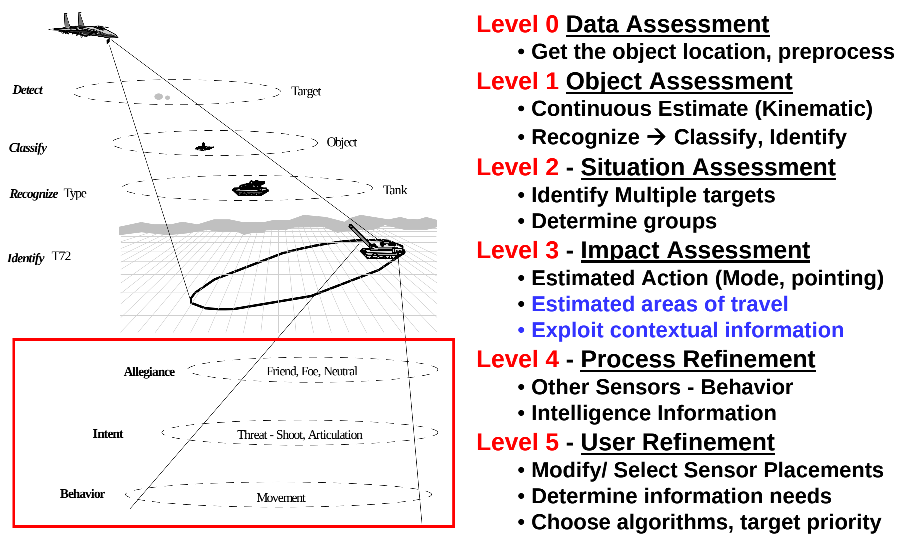

Figure 1. Target tracking and Fusion Process terminology.

1.1. Intent

Intent can be inferred from many situations, such as the target direction or speed. Using contextual information, terrain determines possible avenues of travel. Paths of travel can be determined from trafficability maps.[3, 16, 18] Likewise, using a pursuit / evasion analysis, we can determine possible speeds of the target. Figure 2 shows a detailed terrain map. If the target was suspected to travel from its current location to a garrison (or goal state), it could be inferred as the desired path of travel. However, we can use the "no travel" areas to exclude possible routes and utilize road information as suspected paths, where each pixel location is replaced with intent-based direction map. The target movement prediction is updated based on the measured data and the estimated target trajectory and adjusted with the intent-base selector.

Drummond [11] lists these characteristics of a target: *continuous* **kinematic** (e.g. velocity), continuous **features**, (e.g. signals), discrete **attributes** (e.g. identification), and **categorical** (e.g. size). Intent is a difficult thing to model because it is also difficult to quantify and measure. However the user does desire to know not only the targets, but the suspected target intent. Thus, we forge ahead with an idea for intent modeling. Using the contextual information, we postulate these exogenous constraints :

Roads - available path of travel
High Gradient Terrain – unacceptable movement
Intent Behavior – desired path of travel between current and goal position (e.g. garrison)

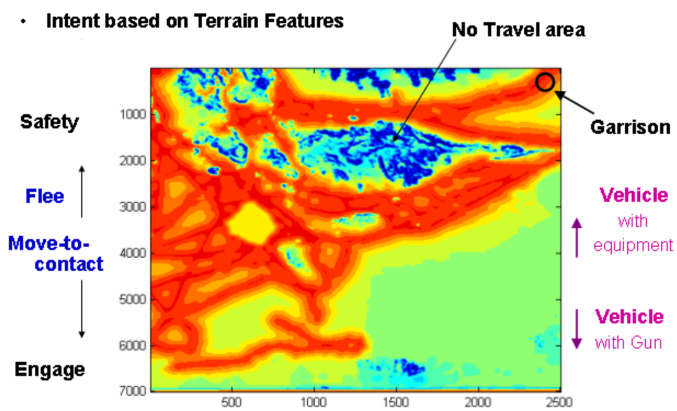

Figure 2. Terrain features for target movement.

If ID information (to distinguish between targets of the same classification) was available, additional information of purpose and potential actions could be inferred (e.g. SCUD goes into stationary hide).

1.2. Target Classification

High range resolution radar (HRRR) attempts to extract a target range profile and to compare it with known target range profile templates for matching, thus achieving target type classification. Range profile is one-dimensional (1D) measurement of target radar reflectivity along the radar to target line-of-sight (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 3A. 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 identifies the target type and at the same time produces the pose at which the range profile is viewed. [8] Figure 3B shows a high resolution range profile.

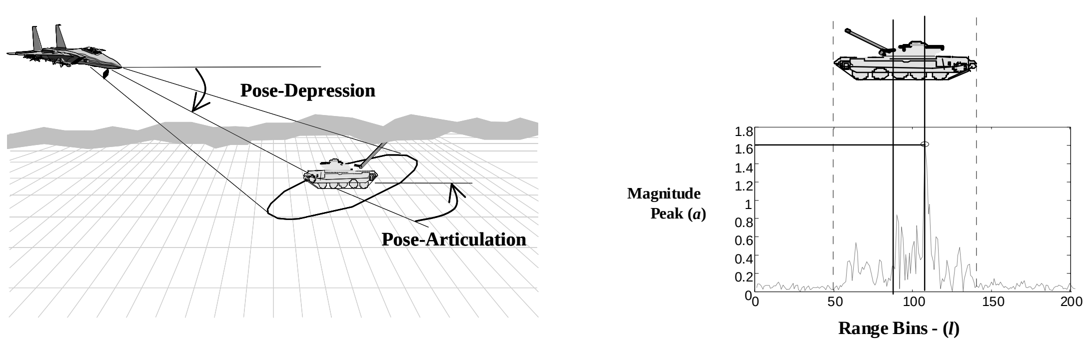

Figure 3. (A) Pose Angle Defined in Terms of Aspect (Articulation) Angles for (B) High Resolution Range Profile

It has been recognized [4] that couplings between tracking and identification systems via pose, kinematic, and association constraints can be exploited to improve performance. 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 identification are considered jointly, we deal with a hybrid space. That is, the target state vector and its 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, if not impossible, 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 maneuvering target.

One approach to solving the technical challenges while meeting the application needs is to explicitly exploit the couplings between tracking and identification systems as well as incorporate intent information. In this paper, we will utilize ground moving target indicator (GTMI) and HRRR measurements as well as digital terrain elevation data (DTED), road map, and goal states as a case study to examine couplings between the target tracking and target identification systems aided by intent information.

2. COUPLINGS BETWEEN TARGET TRACKING AND IDENTIFICATION

In [27], ten couplings of tracking and ID were postulated. The ones that relate to intent are:

A. Type for data association [4]. Target type data can be used to improve associating radar returns with correct 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.

B. Type as kinematic constraints [4]. 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.

E. Pose as a derived measurement [4]. 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 direction measurement of the target velocity vector.

D. Pose as a filter model selector. If the above pose-derived acceleration estimate 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. As an example, Figure 4 shows a target classification for all possible aspects. A eastward movement yields higher confidence, with better pose estimates.

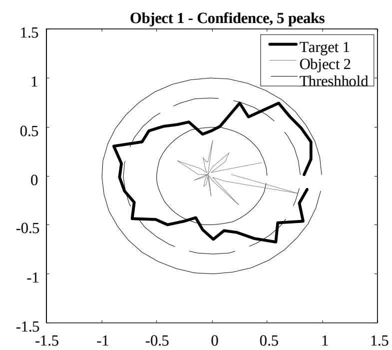

Figure 4. Vehicle separation plot for all aspect angle classifications.

F. Terrain/road-constrained kinematic updating [20]. 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.

H. Kinematics and terrain/road data for narrowing search space. 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.

I. Kinematics to assist target identification. 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.

J. Call for better imaging sensors. The GMTI tracking filter may issue request additional resources such as a video sensor [2, 17, 19] 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, such as for airborne targets. [1, 13, 15]

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

3. FEATURE-AIDED TRACKING

In this section, we utilize the trafficability information (roads, terrain, and goal states) as intent selections of pose estimates, as shown in Figure 5. The performance will vary as a function of the pose estimate selection intent estimates under different operating conditions such as at stop, in steady motion, and making turns.

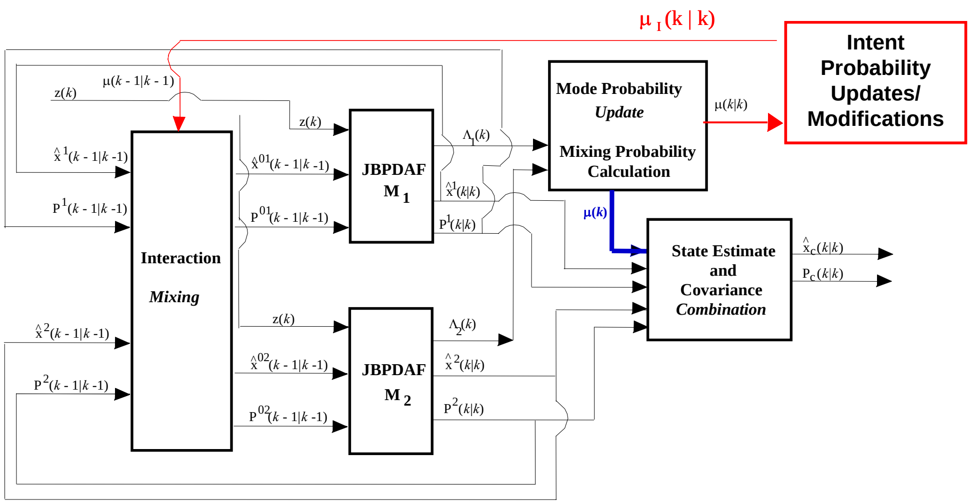

Figure 5. Coupled Target Tracking and Identification with Intent modeling

3.1 Method E: Pose as a derived measurement

In the early work [4], 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 H: Pose-modeled intent from Terrain/Road data

This approach attempts to estimate target pose from terrain data. To implement this approach, the target direction is estimated from available traffic patterns (which can be computed a priori) and intent (which can be based on the target identity). 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. Thus, we seek alternative methods to update pose. 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 [21] 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 [24,26] and applied to maneuvering target tracking with an imaging sensor [25], or trafficability maps, 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 [24, 26] provides an estimate of the unknown intent as well as its estimation error covariance. In this way, not only the orientation-derived intent, but also its estimation error covariance can be incorporated into a second-order extended Kalman filter (EKF) to ensure performance robustness [25].

3.3 Method D: Pose-aided target model selection

The interacting multiple model (IMM) estimator [9] 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 intent estimate from it (Method H), 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 and intent-based model probabilities using either the point-process filtering or by a Bayesian inference method or with a belief classification filter.[27] This external supported IMM algorithm, though being not as fast as Method E 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 identification and pose estimation. Two techniques attempt to reduce the type and pose search space over which the range profile templates will be searched for matching.

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 [4]. This may exclude certain types from being further considered in the tracking filter.

A more applicable technique is to obtain a reliable interval for possible target poses prior to the search in range profile for a given target type [4]. The 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 [6, 20]. 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. Finally, if goal states are known, such as refueling locations, intent information can be used with terrain information to establish movement directions (or a speed-pose velocity vector).

Many databases of range profile templates and techniques of detection and identification have been developed and reported in the literature. [4, 8] To improve their target identification in terms of search speed and successful rate of classification, 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 above. [27]

5. HYBRID MODELING FOR FILTER DESIGN

In this section, we first describe the modeling of kinematic state in a realistic setting with available terrain, road, and goal-state information. We then present the modeling of discrete-valued pose dynamics, measurement process, and estimation.

5.1 Kinematic State Modeling

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). The dynamic behavior of a ground vehicle (wheeled or tracked) is completely described by the set of six-degree-of-freedom (6DOF) equations [27] and its radar observations by a three-dimensional (3D) body reflectivity function. In principle, it is possible to use a 6DOF model to construct a target tracking filter with its attitude variables representing the 3D model for shape or reflectivity recognition.. With 1D HRRR, however, it suffices to use a simplified 6DOF model to describe a ground target motion and a reduced set of variables as the continuous-valued part of the tracking filter design.

5.2 Modeling Discrete-Valued Pose Dynamics and Measurement Process

A 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.

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:

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

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

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

5. 3 Modeling As Discrete-Time Point Process

In the first model, a decision is made by picking up the type and pose corresponding to the set of largest correlation peak matches. 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 $i = 1, \ldots, M$. The HRRR matching outcome is thus mapped into an indicator vector $n(t) = [n_1(t), n_2(t), \ldots, n_M(t)]'$.

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 $D^k = [\, d_{ij}^k \,]$ as:

$$d_{ij}^k = P\{n_j(t) = 1 \mid \rho_i(t) = 1, \phi_k(t) = 1\} \quad \text{with} \quad \sum_{j=1}^{M} d_{ij}^k = 1 \tag{3}$$

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 (direction of travel) based on intent in a probabilistic setting.

Assume that any maneuver will take one of N possible behavior intent vectors $b(t) \in B = \{b_1, b_2, \ldots, b_N\}$ or equivalently $b(t) = B\phi(t)$ with $\phi(t)$ being the indicator vector of $b(t)$, similarly defined as in Eq. (2). Since the maneuvering strategy is almost unknown, the direction change in intent may be modeled as a homogenous Markov chain, specified by its transition probability matrix $\Pi^{\phi} = [\, \pi_{ij}^{\phi} \,]$ as:

$$\pi_{ij}^{\phi} = P\{b(t+1) = b_j \mid b(t) = b_i\} = P\{\phi_j(t+1) = 1 \mid \phi_i(t) = 1\} \quad \text{with} \quad \sum_{j=1}^{N} \pi_{ij}^{\phi} = 1 \tag{4}$$

where the transition matrix is developed form the trafficability map (roads, terrain, and intent paths).

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

$$\pi_{kij}^{\rho} = P\{p(t+1) = p_j \mid p(t) = p_i, b(t) = b_k\} = P\{\rho_j(t+1) = 1 \mid \rho_i(t) = 1, \phi_k(t+1) = 1\}$$

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

where each transition probability can be chosen to match the mean transition time from one pose to another under the maneuver. For a given context, we have modeled both the pose change from ID as well as from the intent.

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:

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

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

$$\phi(t) = [I_{N\times N} \otimes 1_M^{\ T}]\ \xi(t) \quad \text{and} \quad \rho(t) = [1_N^{\ T} \otimes I_{M\times M}]\ \xi(t) \tag{7}$$

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 ξ(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:

$$\pi^{\xi}_{mn} = P\{\xi_n(t+1) = 1 \mid \xi_m(t) = 1\} = P\{\phi_k(t+1) = 1, \rho_j(t+1) = 1 \mid \phi_l(t) = 1, \rho_i(t) = 1\} = \pi^{\rho}_{kij}\pi^{\phi}_{lk} \tag{8}$$

where the indices of (i, j) of ρ(t) and (l, k) of ϕ(t) define m and n in ξ(t), respectively.

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

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

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:

$$\hat{\xi}(t \mid t) = E\{\xi(t) \mid N_t\} \tag{9}$$

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 [24-26] for discrete-time point process can be applied to estimate the composite state and its estimation error covariance matrix. The mode filter consists of measurement updating and prediction equations:

$$\hat{\xi}(t \mid t) = \hat{\xi}(t \mid t-1) + \Gamma_{\xi}[\hat{\xi}(t \mid t-1)]\tilde{n}(t) \tag{10a}$$

$$\hat{\xi}(t+1 \mid t) = (\Pi^{\xi})'\,\hat{\xi}(t \mid t) \tag{10b}$$

where the innovation process and the filter gain are given respectively as:

$$\tilde{n}(t) = n(t) - \Lambda\hat{\xi}(t \mid t-1) \tag{10c}$$

$$\Gamma_{\xi}[\hat{\xi}(t \mid t-1)] = \{diag[\hat{\xi}(t \mid t-1)] - \hat{\xi}(t \mid t-1)\hat{\xi}(t \mid t-1)'\}\Lambda'\{diag[\Lambda\hat{\xi}(t \mid t-1)] - \Lambda\hat{\xi}(t \mid t-1)\hat{\xi}(t \mid t-1)'\Lambda'\}^{-1} \tag{10d}$$

with the initial condition being $\hat{\xi}(0 \mid 0) = E\{\xi(0)\}$.

5. 4 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 noise in the correlation 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 the individual likelihood functions into a vector form:

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

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 $\phi(t)$ and $\rho(t)$ 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 D.

6. RESULTS

The simulation consisted of a terrian map and goal states from which trafficability was assed. The resulting trafficability information was transfromed to an intent map for the likely direction that a target would move. The behavior-movement vector was then incoporated as a selection criteria for the VS-IMM kinematic and classification model weighting. The model was used in conjuctntion with the constant velocity and constant acceleration white noise kinematic models and a Markov intent process model to weight the estimated pose in the prediction process. Figure 6 shows the case where the target moves around the mountain to get to the goal state. The intent was used to facilaite the accurate tracking of the target as it proceeds from the eastward direction to the northern diretcion after a sharp turn. (note Figure 6B is an inversion of Figure 6A due to the plotting capabilities).

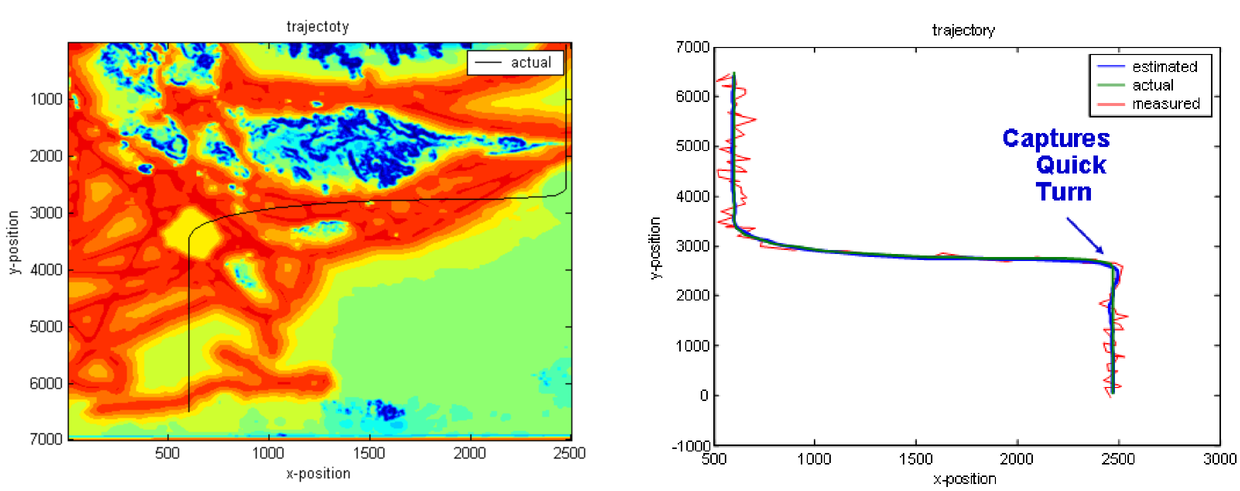

Figure 6. Intent-based target tracking and Identification results.

E. Blasch, “Modeling Intent for a target tracking and identification Scenario,” *Proc. SPIE*, Vol. 5428, April 2004.

6. SUMMARY

In this paper, we developed a method to incorporate intent into a tracking and target identification system to improve performance. We outlined techniques for making use of target pose information to aid target tracking and also techniques to use target kinematics, DTED, road map, and intent information to aid target pose estimation. A hybrid state space modeling was presented to characterize the continuous-valued kinematics and discrete-valued target type, pose (inherently continuous but quantized), and intent behavior.

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