Feature Aided Probabilistic Data Association for Multi-Target Tracking

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Abstract—Feature aided tracking can often yield improved tracking performance over the standard radar tracking with positional measurements alone. However, the complexity of the tracker may dramatically increase due to the inclusion of the target feature state. In this paper, we study the situation where the target feature is a constant or slowly varying parameter with respect to the target state and can be observed together with the target position. We consider using such target feature data for data association which is a significant problem and dominates the outcomes of multi-target tracking in clutter. Extra target discrimination is obtained by computing a joint measurement likelihood which is typically used in a PDA framework. This idea is demonstrated via an example where the target down-range extent measurement is incorporated into a standard IPDA tracker to resolve closely spaced targets in clutter. A simple target extent model is therefore proposed. Our results indicate that when using the proposed feature aided data association process the complexity of data-to-track association can be greatly reduced. Moreover, the tracking performance of the IPDA tracker is greatly improved.

Keywords: Data association, target feature measurement, target extent, feature aided tracking.

I. INTRODUCTION

In many radar/sonar target tracking applications, target information will be typically extracted from a noisy position measurement sequence. In the presence of multiple, perhaps closely spaced, targets with clutter and sensor noise, it is often difficult to point out which measurement corresponds to which target from a single scan of sensor observations. Sophisticated techniques, such as MHT [1], J(I)PDA [2], [3] and others [4], are often required to perform exhaustive data association to resolve the problem to some degree. However, tracker complexity may be an issue.

Enhanced data association can be performed by using additional information from measurements associated with some target features, which is sometimes known as feature aided tracking in the target tracking literature. In general, a target feature can be referred to a target signature – e.g., a high resolution sensor observation profile, a target type from a finite set of discrete classes, or some measurable parameters related to target behaviors distinguishable from disturbance in the observation domain, etc.

A method is presented in [5], which integrates target class information into the data association process using 2-D as well as multiple multiframe assignments. The multiframe association likelihood is developed to include classification results based on a “confusion matrix” that specifies the accuracy of the target classifier. Significant data association improvement has been achieved compared to the case of using kinematic information alone.

Using target features for track association under MAP metrics is proposed in [6], where methods for incorporating independent and dependent feature measurements were discussed.

Incorporating high resolution range measurements (HRR) and GMTI measurements for tracking ground moving targets is presented in [7], where a Gaussian mixture model is used to approximate the signature (HRR profile) of the underlying target. In an earlier work [8], the signature was extracted using wavelets features from HRR data. The incorporation of the target spectral signature into the target detection process via a recursive likelihood ratio test, and therefore in the computation of the track score function, was presented in [9], where the track score is used in a multi hypothesis tracker. An extended discussion of this topic is given in [10]. A generic feature aided tracking method was described in [11].

In this work, we consider a class of target features which are continuous valued and can be modeled as either constant or slowly varying parameters with respect to the target state. The feature values from different targets may be different but are unknown. However, in the short term these values are near constant and are distinguishable from those which are from clutter. Some examples in radar/sonar tracking applications are target Doppler, range extent and detected signal amplitude. The consistency of these target features provide extra target discrimination power and help suppress false tracks. However, the literature suggests that one has to use nonlinear filters in the process to cope with the inclusion of target features in a typical
target kinematic state tracking system. Such examples may be found in [12]–[16], where the extended Kalman filter (EKF) has to be used. While algorithm complexity may increase, the use of EKFs may potentially introduce filter instability and performance issues which are inherent to the EKF [12], [16], [17].

In this paper, an alternative approach that uses target feature measurements for data association (rather than state estimation), is proposed. We refer to this approach as the target feature aided data association. The underlying idea is implemented in an IPDA tracker. The major advantage of target feature aided data association is that it can greatly simplify the requirements of the system while enhanced data association is performed. An early work of this type, where target Doppler measurements for data association (rather than state estimation), is proposed. We refer to this approach as the target feature aided data association problem is considered for data association, was presented in [18].

The rest of the paper is arranged as follows. In the next section, the target feature aided data association problem is formulated in a PDA framework. The justification of the proposed approach is also given. In Section III, an application example, where target down-range extent measurements are used for feature aided PDA, is presented. A tracking performance comparison is given in Section IV which is followed by the conclusions in Section V.

II. FEATURE AIDED PDA

A. The Problem

Without loss of generality, we model the trajectory of an individual target $\tau$ by

$$x_{k+1}^\tau = F_k x_k^\tau + \nu_k^\tau, \quad \nu_k^\tau \sim \mathcal{N}(0, Q_k)$$  \hspace{1cm} (1)

where $x_k^\tau$ denotes the kinematic state of the $\tau$th target at time $k$. $F_k$ is a known system transition matrix and $\nu_k^\tau$ is zero mean white Gaussian\footnote{Here we use the notation $\mathcal{N}(x, \bar{x}, \Sigma)$ to signify a Gaussian random variable $x$ with mean $\bar{x}$ and covariance $\Sigma$.} noise with covariance $Q_k$. For example, in a 2D Cartesian coordinate system, the target state may typically be a vector of 4 components consisting of position and velocity for each axis, i.e.,

$$x_k^\tau = \begin{bmatrix} x_k & \dot{x}_k & y_k & \dot{y}_k \end{bmatrix}^T.$$ \hspace{1cm} (2)

At each sampling time $k$, a set of sensor measurements $Z_k = \{ z_{k,1}, \cdots, z_{k,m_k} \}$ are received, which includes returns from both targets and clutter. We use $Z_k^\tau$ to denote the sequence of sensor measurement sets up to time $k$, i.e.,

$$Z_k^\tau = \{ Z_1^\tau, \cdots, Z_k^\tau \}.$$  \hspace{1cm} (3)

where the target position measurement is given by

$$z_{k,i}^p = H x_k^{\tau} + \omega_k^{\tau}, \quad \omega_k^{\tau} \sim \mathcal{N}(0, R_k^p)$$  \hspace{1cm} (4)

$H$ is a known matrix and $R_k^p$ is the covariance of the position measurement noise.

Similarly, the target feature measurement $z_{k,i}^f$ may be written as

$$z_{k,i}^f = h(x_k^{\tau}) + n_{k,i}^f$$

(5)

where $h(x_k^{\tau})$ is the feature state of target $\tau$ at time $k$, and is often a function of target kinematic state $x^\tau$. $R_k^f$ denotes the covariance of the target feature measurement noise.

As mentioned previously, the target feature we will consider is a continuous parameter. Furthermore, we assume that

1) the target feature state $x_{k,f}^\tau = h(x_k^{\tau})$ is a time-invariant (or slow-varying) parameter and can be modeled as

$$x_{k,f}^\tau = h(x_{k-1,f}^\tau) + \nu_{k,f}^\tau, \quad \nu_{k,f}^\tau \sim \mathcal{N}(0, Q_k^f)$$  \hspace{1cm} (6)

2) the feature measurement of a target is independent of its position measurement, which implies that

$$p(z_{k,i}^p, z_{k,i}^f | Z_k^\tau) = p(z_{k,i}^p | Z_k^\tau)p(z_{k,i}^f | Z_k^\tau)$$  \hspace{1cm} (7)

where $Z_k^\tau$ is position and feature measurement sequences up to time $k$ respectively.

The general target tracking problem is to find the posterior pdf $p(x_k^\tau | Z_k^\tau)$ based on the measurement sequence $Z_k^\tau$, which can be expressed in a Bayesian recursion as

$$p(x_k^\tau | Z_k^\tau) = p(x_k^\tau | Z_{k-1}^\tau)$$

$$= \int p(Z_k^\tau | x_k^\tau)p(x_k^\tau | Z_{k-1}^\tau) dx_k^\tau$$  \hspace{1cm} (8)

Under linear Gaussian assumptions, the term $p(x_k^\tau | Z_{k-1}^\tau)$ in (8) can be evaluated straightforwardly. However, the overall solution is heavily dependent on the outcome of the data association process which has to be performed to resolve the uncertainty in the measurement domain. In other words, the evaluation of the likelihood term $p(Z_k^\tau | x_k^\tau)$ is a crucial part of the estimation recursion process. Various tracking techniques distinguish themselves largely in the evaluation of this term.

Note that we do not include the target feature state as part of target state in the state estimation process. Our intention is merely to use the target feature measurements for data association. This is based on the following observations:

1) The inclusion of the target feature state will likely result in a highly nonlinear system, which increases the filter complexity considerably.

2) Data association is the key issue in multi-target tracking in clutter.

We will explore this idea further in the next subsection.

B. The Algorithm

In this subsection, our idea of incorporating target feature measurement for data association is illustrated using the standard PDA/IPDA framework. The work presented below aims to justify the effectiveness of the proposed method rather than to provide a detailed derivation which may be found in [2], [19].
1) Target state estimation process:
Let $z_{k,i}$ denote the measurement of target $\tau$ at time $k$, the posterior pdf is given by

$$
p(x_k^\tau | z_{k,i}, Z^{k-1}) = \frac{p(z_{k,i} | x_k^\tau, Z^{k-1}) p(x_k^\tau | Z^{k-1})}{\int p(z_{k,i} | x_k^\tau, Z^{k-1}) p(x_k^\tau | Z^{k-1}) dx_k^\tau} = \frac{p(z_{k,i}^p | x_k^\tau, Z^{k-1}) p(x_k^\tau | Z^{k-1})}{p(z_{k,i}^p | Z^{k-1})} \approx \frac{p(z_{k,i}^p | x_k^\tau, Z^{k-1})}{p(z_{k,i}^p | Z^{k-1})}$$

where (9) to (10) is based on the approximation

$$p(z_{k,i}^f | x_k^\tau, Z^{k-1}) \approx p(z_{k,i}^p | Z^{k-1})$$

which is from the fact that the value of the target feature state is constant over $(k-1,k]$ regardless of the change in the target kinematic state (6), i.e.,

$$h^f(x_k^\tau) = h^f(x_k^{\tau-1})$$

In other words, compared to the feature measurement noise, the feature state process noise is negligible. The approximation deems that zero “new” information about the target kinematic state is obtained from the target feature measurement and therefore eliminates the feature measurement in the state estimation recursion. The approximation is good when the target feature state is independent of the target kinematic state or is only weakly correlated.

2) Measurement-to-track association process:
Let $\rho_k = \{\rho(z_{k,1}), \ldots, \rho(z_{k,m_k})\}$ denote the set of joint clutter densities at the locations of measurements $Z_k = \{z_{k,1}, \ldots, z_{k,m_k}\}$. The standard PDA defines the events

$\theta_0$ : all validated measurements are from clutter;
$\theta_i$ : the $ith$ validated measurement is from the target, and all others are from clutter.

It can be shown that the data association probabilities can be evaluated as follows,

$$P(\theta_i | Z^k) \triangleq \beta_{k,i} = \frac{(\rho(z_{k,i})^\tau)^{-1} p(z_{k,i} | \theta_i, Z^{k-1}) P(\theta_i | Z^{k-1})}{\sum_{j=1}^{m_k} (\rho(z_{k,j})^\tau)^{-1} p(z_{k,j} | \theta_j, Z^{k-1}) P(\theta_j | Z^{k-1})}$$

$$i = 0, 1, \ldots, m_k,$$

where $\rho(z_{k,i})^\tau \triangleq \rho(z_{k,i}^p)\rho(z_{k,i}^f)$

is the joint clutter density at $z_{k,i}$ and

$$p(z_{k,i} | \theta_i, Z^{k-1}) \triangleq p(z_{k,i}^p | \theta_i, Z^{k-1}) p(z_{k,i}^f | \theta_i, Z^{k-1}) = \Lambda_{k,i}^p \Lambda_{k,i}^f$$

is the joint measurement likelihood that $z_{k,i}$ is from target, where

$$\Lambda_{k,i}^p \sim \mathcal{N}(z_{k,i}^p | \hat{z}_{k,i}^p, S_k^p)$$

$$\Lambda_{k,i}^f \sim \mathcal{N}(z_{k,i}^f | \hat{z}_{k,i}^f, S_k^f)$$

The joint measurement likelihood is expected to influence the probability of data association significantly as we suppose that the feature measurement from a target is distinguishable to that from clutter even though similar values of the position measurement likelihood may be observed.

Following (12), it can be easily shown that for the (I)PDA algorithm, the data association probabilities are given by

$$\begin{align*}
\beta_{k,0} &= \frac{1 - PD_PG}{1 - PD_PG \left(1 - \sum_{j=1}^{m_k} \frac{\Lambda_{k,j}^p \Lambda_{k,j}^f}{\rho(z_{k,j}^p)\rho(z_{k,j}^f)}\right)} \\
\beta_{k,i} &= \frac{1 - PD_PG \left(1 - \sum_{j=1}^{m_k} \frac{\Lambda_{k,j}^p \Lambda_{k,j}^f}{\rho(z_{k,j}^p)\rho(z_{k,j}^f)}\right)}{i = 1, \ldots, m_k} \quad (14)
\end{align*}$$

where $PD$ and $PG$ are the detection probability and the probability that the target measurement is in the gate respectively.

As an extension to standard PDA, the probability of target existence is calculated in the IPDA algorithm [19], [20]. It is assumed that the existence of a target may exhibit two mutually exclusive and exhaustive states

$$\chi_k = \begin{cases} 1, & \text{target exists and is detectable.} \\ 0, & \text{target does not exist.} \end{cases} \quad (15)$$

and the transition between these two states are modeled as a two-state Markov chain with transition probabilities

$$\pi_{ij} \triangleq P(\chi_k = j | \chi_{k-1} = i), \quad i, j \in \{0, 1\}$$

We can show that in this case, the probability of target existence is given by

$$P(\chi_k | Z^k) = \frac{(1 - \delta_k) P(\chi_k | Z^{k-1})}{1 - \delta_k P(\chi_k | Z^{k-1})} \quad (16)$$

where

$$\delta_k = PD_PG \left(1 - \sum_{i=1}^{m_k} \frac{\Lambda_{k,i}^p \Lambda_{k,i}^f}{\rho(z_{k,i}^p)\rho(z_{k,i}^f)}\right) \quad (17)$$

and the predicted probability of target existence is calculated using Markov chain model as follows.

$$P(\chi_k | Z^{k-1}) = \pi_{01} P(\chi_{k-1} | Z^{k-1}) + \pi_{11} P(\chi_{k-1} | Z^{k-1}) \quad (18)$$

3) Remarks:

a) In order to evaluate the data association probabilities, the target feature state will also be required
to be estimated online, which can be performed in the PDA framework.

b) Our proposed method may be extended straightforwardly to handle the case of multiple independent target features.

III. AN APPLICATION EXAMPLE

There are a number of measurable target features, such as target Doppler, down-range extent, and signal-to-noise ratio, etc. They can be suitable for the data association method presented in this paper if certain assumptions are met. It is understood that most of them exhibit a strong nonlinear relationship with the target kinematic state and will likely increase the tracker’s complexity significantly if they are incorporated into the state estimation process. In this section, target down-range extent is used as the feature to demonstrate our proposed method.

A. Target Down-Range Extent Model

In radar or sonar tracking, target down-range/cross-range extent can often be measured after raw data processing. The observed target extent may be modeled as a slowly varying parameter in some situations such as high data rate radar or active sonar underwater target tracking. In [12] the target extent was modeled as an ellipse and in [13] as rectangle. In this work, we simply assume that the underlying target body is rigid and the length of a target, denoted by $L$, is defined as the body length along target motion direction. We have

$$L_{k+1} = L_k + n_{L,k}$$

$$n_{L,k} \sim \mathcal{N}(n_{L,k}; 0, Q^L_k),$$

(19)

A 2D graphical illustration of the relationship between the target length and its down-range extent is given in Figure 1.

Denoting by $z^e_k$ the measurement of target down-range extent, we can express the target down-range extent measurement as

$$z^e_k = L_k |\cos \phi| + n_{e,k}$$

$$n_{e,k} \sim \mathcal{N}(n_{e,k}; 0, R^L_k)$$

(20)

where $\phi$ is the angle between target heading and the line of sight. Let the target velocity be $X_v = [x_k, y_k]'$ and target position $X_p = [x_k, y_k]'$, then we have

$$\cos \phi = \frac{\langle X_v, X_p \rangle}{||X_p|| \cdot ||X_v||}$$

(21)

where $\langle \cdot, \cdot \rangle$ signifies vector inner product. Note that the sign of $\cos \phi$ is negative if the target is heading away from the sensor.

In the system of (19) and (20), target length $L_k$ is an unknown constant and we must estimate it online in order to extract useful information from target extent measurements, which can lead to a much more complex tracker as in [12].

B. Target Extent Aided IPDA

In our approach, target extent is modeled as a slowly varying parameter (with respect to its kinematic state). Let $x^e_k$ be the extent state of the target. In view of (20) and (5), we may write

$$x^e_k = h(x_k) = L_k |\cos \phi|$$

In particular, we assume that

$$x^e_k = x^e_{k-1} + \nu^e_k, \quad \nu^e_k \sim \mathcal{N}(\nu^e_k; 0, Q^L_k)$$

(22)

As indicated in the previous section, the algorithm is exactly the same as the standard IPDA except that the target extent measurement likelihood has to be computed for the joint measurement likelihood in (13). For such a purpose, the target extent is also estimated and recursively updated using (22), (20) and (14) in this PDA framework.

IV. PERFORMANCE COMPARISON

A. Simulation Scenario

The advance of the proposed approach is demonstrated in a multiple parallel motion target tracking scenario. Three constant velocity targets are heading to north-eastern direction away from sensor located at the origin with identical velocities $X_v = [10, 6]'$ m/s in a 2D Cartesian coordinate system. The targets are present throughout the simulation and are observed by a sensor at a sampling rate $T = 1$ second over 100 scans. As shown in Figure 2, the targets are spaced in parallel with a constant distance of 140 meters between targets 1 and 2 and targets 2 and 3 respectively. As the distance is less than the diameter of the sensor resolution cell, these targets are considered to be closely spaced targets.

The target position measurement sequence is generated using (4) with a standard deviation for the measurement noise of 40 meters in both the x and y directions and a detection probability $P_D$.

The target down-range extent measurement sequence is generated using (20), where the lengths of targets 1 and 3 are assumed to be identical of 10 meters and 11 meters for target 2. The standard deviation of target extent measurement error is 1 meter.

We assume that false position measurements are of Poisson distribution with density $\lambda$ and false extent measurements are uniformly distributed over the field of interest.

The underlying IPDA tracker was implemented with a simple one-point track initiation unit which uses all position measurements received at the current scan to initiate new tracks at every scan. While a position measurement will be used as the initial position of a new track, the initial velocity
of a new track will be assumed to have a zero-mean Gaussian distribution with standard deviation set to the maximum target speed which is assumed to be known to be 20 m/s.

The probability of target existence serves as a track quality measure for track maintenance. Each new track is initially assigned a small probability of target existence (e.g., 0.05). A track will be confirmed and output if its probability of target existence exceeds a threshold (e.g., 0.9) and a track will be deleted if its probability of target existence is below a threshold (e.g., 0.001). Two tracks, represented by their state estimates $\hat{x}_{1|k}$ and $\hat{x}_{2|k}$, and covariances $P_{1|k}$ and $P_{2|k}$ respectively, are merged when

$$
(\hat{x}_{1|k} - \hat{x}_{2|k})'(P_{1|k} + P_{2|k})^{-1}(\hat{x}_{1|k} - \hat{x}_{2|k}) \leq \varepsilon
$$

where $\varepsilon = 5$.

Note that all these thresholds can be different in different trackers. In this experiment, we choose thresholds to maximize the number of confirmed true tracks while maintaining zero confirmed false tracks.

In order to compare data association performance and thus tracking performance, the following measures are used in the comparison.

1) The probability that a confirmed track is correctly associated to a measurement. In the PDA framework, this probability is the data association probability that the confirmed track is following the ground truth measurement.

2) The percentage of confirmed true tracks.

1000 Monte Carlo runs were performed for each of the following cases:

Case 1: Standard IPDA, $\lambda = 0$, $P_D = 1$.
Case 2: Target extent aided IPDA, $\lambda = 0$, $P_D = 1$.
Case 3: Target extent aided IPDA, $\lambda = 10^{-5}/m^2$, $P_D = 0.9$.

The sensor observed position measurements and extent measurements in Case 3, both accumulated over 100 scans, are illustrated in Figures 3 and 4 respectively.

B. Results and Discussions

The average number of measurements in a track’s (position) gate is summarized in Table I, which highlights the degree of ambiguity in this problem – as measurements from different targets can fall in the same sensor resolution cell, they are all potential measurements from the target. The ambiguity of in-gate measurements will, in turn, lead to a larger gate volume in the subsequent scans as shown in Case 1. However, by incorporating target extent measurements, as indicated in Case 2, the number of in-gate measurements can be reduced due to correct measurement-to-track associations. The average number of in-gate measurements increases in Case 3 indicating the even more severe data association ambiguity due to the presence of dense clutter measurements and non-unity target
detection probability.

Table I

<table>
<thead>
<tr>
<th></th>
<th>Track 1</th>
<th>Track 2</th>
<th>Track 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>2.2075</td>
<td>2.9497</td>
<td>2.1655</td>
</tr>
<tr>
<td>Case 2</td>
<td>1.7416</td>
<td>2.5166</td>
<td>1.7303</td>
</tr>
<tr>
<td>Case 3</td>
<td>2.5701</td>
<td>3.3102</td>
<td>2.5169</td>
</tr>
</tbody>
</table>

In this scenario, the tracking of target 2 is more challenging as the underlying track-gate always includes measurements from the other two targets, which introduces measurement-to-track association ambiguity at all times.

Figure 5 presents the statistics of true track confirmation on target 2, where we note that there is no confirmed track in Case 1 at all. As we observed, the probability of target existence for track 2 is lower than those for false tracks and therefore track 2 cannot be confirmed as we must eliminate false tracks from consideration.

The probability of correct measurement association for target 2 is given in Figure 6 and the probabilities that track 2 is associated with a particular measurement is plotted in Figure 7. Note that, as no confirmed track was present in Case 1, the probabilities plotted in these figures (for Case 1) are from unconfirmed tracks for comparison purposes.

Figure 6. The probability that the track corresponding to target 2 has been associated with the correct measurement.

Figure 7. Comparison of Cases 1 and 2 for probabilities of track 2-to-measurement association.

Result Discussions:
- Figure 5 (for Cases 2 and 3) demonstrates a significant improvement in terms of the number of confirmed true tracks. Without confirming a false track, the number of confirmed true tracks in Case 2 is around 90% after scan 40, although this figure will drop when clutter is introduced (in Case 3). It was also observed that when the target extent measurement error increases, the percentage of true tracks confirmed will decline. On the other hand, there is no confirmed true track in Case 1 with position measurements alone. This trend is also reflected in Figure 6, where the data association probabilities that the true measurement is used for updating track 2 are plotted versus scan.
- The improved data association performance obtained by incorporating target extent measurements is further demonstrated in Figure 7. With target extent measurements, the probability that track 2 is associated with true measurements is above 0.95 (Case 2), while the probability that track 2 is associated with the other two measurements is close to zero. In contrast, without target extent aided data association, the above probabilities are more or less close to each other.
- From Figure 6, we can see that without target extent aided data association, the unconfirmed track 2 has a less than 50% chance of following a true measurement and this leads to the similar probabilities that the underlying track...
is associated to a measurement as seen from the upper sub-figure of Figure 7. This causes a track to frequently misuse measurements which results track swaps.

- The preliminary simulation results suggest that the performance of the target extent aided PDA will depend on 1) false extent measurement density; 2) extent measurement noise; and 3) the separations between extent measurements from different targets. Certainly, there are performance limits with respect to these issues and we will address them in our future publications.

V. CONCLUSIONS

In this paper, a method that makes use of the consistency of target related parameters to perform feature aided data association in the (I)PDA framework was presented. The approach adds additional discrimination from target feature measurements for measurement-to-track association by computing a joint likelihood function. The performance of this target feature aided IPDA is demonstrated via an example of incorporating target extent measurements into a positional IPDA tracker. Results show that the target extent aided IPDA enhances data association performance significantly due to the provision of additional discrimination for measurement-to-track association.

It is expected that the proposed method will work for even more complex situations such as multiple maneuvering target tracking in clutter. The key message here is that target feature measurements can be wisely incorporated for multi-target tracking in clutter using kinematic measurements. It can generate a practical solution which results in significant performance improvement without significantly increasing the tracker’s computational burden.

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