Multi-Target Tracking with Partially Unresolved Measurements

Daniel Svensson
Dept. Signals and Systems
Chalmers Univ. of Technology
Gothenburg, Sweden
daniel.svensson@chalmers.se

Martin Ulmke
Dept. SDF
Fraunhofer FKIE
Wachtberg, Germany
martin.ulmke@fkie.fraunhofer.se

Lars Danielsson
Active Safety Electronics
Volvo Car Corporation
Gothenburg, Sweden
ldanie25@volvocars.com

Abstract: The problem of limited sensor resolution, although usually ignored in target tracking, occurs in multi-target scenarios whenever the target distance falls below the size of the sensor resolution cell. Typical examples are the surveillance of aircraft in formation, and convoy tracking for ground surveillance. Ignoring the limited sensor resolution in a tracking system may lead to degraded tracking performance, in particular unwanted track-losses. In this paper, an extension of the resolution model by Koch and van Keuk to the case of arbitrary object numbers is discussed. The model is incorporated into the Joint Probabilistic Data Association Filter (JPDAF) and applied to a simulated scenario with partially unresolved targets.

1 Introduction

Generally, target tracking is separated into data assignment and kinematic filtering (see e.g. [BP99]). For both steps appropriate sensor models have to be developed which are simple enough to be feasible for a tracking algorithm, however, still cover the essential features important to tracking such as measurements errors and resolution properties. When the distance between targets is small compared to the measurement error, the assignment between targets and detections becomes ambiguous, leading to a fast growing number of possible data assignments. When, on the other hand, the target distance becomes smaller than the size of the resolution cell, there is an additional source of ambiguity as a given detection may result from the measurement of two or more targets. Usually, this resolution problem is neglected in the design of target tracking algorithms. In many situations, this is a reasonable assumption, but there are important cases when the resolution capabilities of the sensor cannot be ignored [DF94]. Typical examples of when objects are closely spaced in relation to the sensor resolution is the tracking of aircraft in formation, and convoy tracking for ground surveillance. For such applications, ignoring the limited sensor resolution may lead to degraded tracking performance, in particular due to premature deletion of tracks.

The ability of a sensor to resolve several objects can be described by the resolution probability. An important aspect of sensor resolution is its dependence on the sensor–target distance. This property has been covered in the resolution model by Koch et al. [KvK97] but is absent in traditional grid-based approaches [CBS84, MCC87]. Until recently, to the best of our knowledge, the existing resolution models have been limited to only two targets. The present paper describes a generalization of the resolution model [KvK97] to arbitrary target numbers and the incorporation of the model into the Joint Probabilistic Data Association Filter (JPDAF) [FBSS83]. We also present results of a simulated scenario with resolution limitations, where the JPDA filter with the proposed resolution model is shown to yield better tracking results than the ordinary JPDAF.

2 Problem formulation

The ultimate goal of a tracking filter is to calculate the posterior density $p\big(\mathbf{x}_k \big| \mathbf{Z}^k\big)$ of the joint target state vector $\mathbf{x}_k$, given all measurements $\mathbf{Z}^k$ up to, and including, the current time index k. For the N-target case, the joint target states is described as

$$\mathbf{x}_k = \Big[\big(\mathbf{x}_k^{(1)}\big)^T \quad \big(\mathbf{x}_k^{(2)}\big)^T \quad \ldots \quad \big(\mathbf{x}_k^{(N)}\big)^T \Big]^T , \tag{1}$$

where $\mathbf{x}_k^{(i)}$ is the state of target i. Further, the collection of measurements up to time index k is given by the set $\mathbf{Z}^k = \big\{\mathbf{Z}_1, \mathbf{Z}_2, \ldots, \mathbf{Z}_k\big\}$.

In order to perform the calculation of the posterior density in the presence of resolution uncertainty, we need to model the measurements from an unresolved group of targets (henceforth called group target), and to describe the probability of resolution for that group. We also need to model the motion of the targets. At time index k, a sensor produces M_k observations which are either target-generated or spurious. As is common in most tracking algorithms, we assume that the clutter measurements are described by a spatially homogeneous Poisson process with intensity λ.

Group measurement model and process model: We assume a simple model for the measurement of an unresolved group of targets (henceforth referred to as a group measurement). The model does not capture the true nature of a group measurement, but serves the purpose of illustrating the proposed framework. In general, more refined group measurement models can be used within the framework.

The assumed model states that a group measurement can be described as a measurement of the group center, where the center point is given by the arithmetic mean of the involved target states. That is, for an unresolved group of n_g targets (possibly one), whose state vectors are gathered in the joint vector $\mathbf{x}_k^g$, their group measurement $\mathbf{z}_k^{t,(j)}$ is described by

$$\mathbf{z}_k^{t,(j)} = \mathbf{H}_{n_g} \mathbf{x}_k^g + \mathbf{u}_k^{g,n_g} , \tag{2}$$

where $\mathbf{H}_{n_g} = [\mathbf{H}, \cdots, \mathbf{H}]/n_g$ and where $\mathbf{u}_k^{g,n_g} \sim \mathcal{N}\big(\mathbf{0}, \mathbf{R}_k^{n_g}\big)$ is the measurement noise for an n_g-target group. Typically, the measurement noise covariance matrix increases with increased number of targets in the group.

The (potentially correlated) motion of the multiple targets are described, as usual, by a discrete time Gauss-Markov process model.

Resolution model: The multi-target resolution model of [SUD10] describes the resolution probability for a group of arbitrary, but known, number of targets, and it is a generalization of the two-target model in [KvK97]. For a certain pair of targets $\mathbf{x}_k^{(i)}$, $\mathbf{x}_k^{(j)}$, the probability that they are unresolved is, according to [KvK97],

$$P_u(\mathbf{x}_k^{(i)}, \mathbf{x}_k^{(j)}) = \prod_{l=1}^{N_{\text{res}}} e^{-\ln(2)\left(\frac{\Delta^{i,j} x_l}{\alpha_{x_l}}\right)^2}, \tag{3}$$

where N_{res} is the dimension of the measurement space (2 for range and azimuth), $\Delta^{i,j} x_l$ is the distance between the predicted positions of targets i and j in dimension x_l, and α_{x_l} describes the resolution capabilities of the sensor in dimension x_l. The dimension can for example be $x_l = r$ for range, or $x_l = \varphi$ for azimuth angle. The probability $P_u(\mathbf{x}_k^{(i)}, \mathbf{x}_k^{(j)})$ can also be written as a scaled multivariate Gaussian [KvK97]

$$P_u(\mathbf{x}_k^{(i)}, \mathbf{x}_k^{(j)}) = \left|2\pi \mathbf{R}_{u,N_{\text{res}}}\right|^{1/2} \mathcal{N}\big(0; \Delta^{i,j}\mathbf{x}_k, \mathbf{R}_{u,N_{\text{res}}}\big), \tag{4}$$

where $\Delta^{i,j}\mathbf{x}_k$ is a vector with the distances between the target positions in each dimension, and $\mathbf{R}_{u,N_{\text{res}}} \propto \operatorname{diag}\{\alpha_{x_1}^2, \ldots, \alpha_{x_{N_{\text{res}}}}^2\}$. For range and azimuth measurements, and small $\Delta\varphi$, this can easily be generalized to Cartesian coordinates by a rotation by the average angle $\bar{\varphi} = (\varphi^{(1)} + \varphi^{(2)})/2$. The Gaussian shape of the resolution probability will allow Kalman filter-like updates of the probability density function (pdf).

To extend the model to arbitrary target numbers, we assume the resolution probability to be pairwise independent. Resolution events can be described by a graph representation [SUD10], where each node (vertex) in the graph represents a target. Two targets are then mutually unresolved if they are connected by an edge in the graph. Further, a group of targets is unresolved if there exists a walk in the graph through all target vertices. Consequently, there are several graphs which generate the same target group. The probability for a group of unresolved targets as well as for the whole graph, or "subgroup pattern", $\mathcal{V}$, can be expressed in terms of products of the probabilities for being unresolved or resolved, P_u or $(1 - P_u)$, respectively [SUD10]. As one exploits a "negative" sensor output for estimating the multi-target state, it is sometimes denoted as "negative information" update.

3 Data Assignment

In standard tracking approaches [BP99], the unknown assignment between targets and detection are treated as hidden variables, and the updated pdf is marginalized over all feasible data assignments. In the case of possible unresolved measurements, the sum over assignments is split into two steps: first we sum over all possible target subgroup patterns $\mathcal{V}$, defined above. Applying Bayes theorem, the sum is:

$$p\big(\mathbf{x}_k \big| \mathbf{Z}^k\big) \propto \sum_{\mathcal{V}} \Pr\left\{\mathcal{V}\big|\mathbf{x}_k\right\} p\big(\mathbf{Z}_k\big|\mathcal{V},\mathbf{x}_k\big) p\big(\mathbf{x}_k\big|\mathbf{Z}^{k-1}\big) \tag{5}$$

In a second step, we marginalize the likelihood function in the sum (5) above over all data assignments $d \in \mathcal{D}(\mathcal{V})$ for a given subgroup pattern $\mathcal{V}$:

$$p\big(\mathbf{Z}_k\big|\mathcal{V},\mathbf{x}_k\big) = \sum_{d\in\mathcal{D}(\mathcal{V})} p\big(\mathbf{Z}_k\big|\mathcal{V},d,\mathbf{x}_k\big) \Pr\left\{d|\mathcal{V},\mathbf{x}_k\right\}. \tag{6}$$

Explicit expression for the pdf and likelihood function are given in [SUD10].

4 JPDA filter incorporation

Under the assumptions mentioned above (linear, Gaussian measurement and process models) the updated multi-target pdf, eventually, is given as:

$$p\big(\mathbf{x}_k\big|\mathbf{Z}^k\big) = \sum_{\mathcal{V}} \sum_{u\in\mathcal{U}(\mathcal{V})} \sum_{d\in\mathcal{D}(\mathcal{V})} c^{\mathcal{V},u,d} \mathcal{N}\big(\mathbf{x}_k; \mathbf{x}_{k|k}^{\mathcal{V},u,d}, \mathbf{P}_{k|k}^{\mathcal{V},u,d}\big), \tag{7}$$

where the normalized scaling factors $c^{\mathcal{V},u,d}$ depend on the data association probability $\Pr\{d\big|\mathcal{V},\mathbf{x}_k\}$, the graph and state vector likelihood $p\big(\mathbf{Z}_k\big|\mathcal{V},d,\mathbf{x}_k\big)$ and the graph probability $\Pr\{\mathcal{V}\big|\mathbf{x}_k\}$. The sum over $u \in \mathcal{U}$ comes from the so-called "negative-information" update, discussed in Sec. 2, where each update with a resolved pair of targets doubles the number of Gaussian components.

The standard JPDA filter makes a Gaussian approximation of a Gaussian mixture at each time step. Similarly, a JPDA filter with a resolution model should make a Gaussian approximation of the mixture in (7). In principle, JPDA approximations on different level are possible [SUD10]. Here, we first perform a moment matching over the data association hypotheses for a given graph, and then make a second moment matching over the set of graphs, after negative information update.

5 Simulation Results

We study a simple simulated tracking example with two targets. In the scenario, the targets are first approaching each other, then move in parallel, and finally separate (see Fig. 1). Due to limited sensor resolution, the two targets are not always resolved. Since the targets are closely spaced, there is a big risk of track coalescence in the ordinary JPDA filter. Example output from the JPDA filter without and with resolution model incorporation can be found in Fig. 1. As seen in the figures, the tracks from the JPDA filter with resolution model are more separated, due to a better description of the received measurements. The targets move with a constant speed of 5m/s, and the true separation of the targets is 40m in the parallel section. The sensor resolution cell is chosen as a square with edge length 40m in Cartesian coordinates.

For the evaluation of the tracking performance, we use as a first criterion the Mean Optimal Subpattern Assignment (MOSPA) measure [SVV08], which is a measure that disregards target identity and thus only considers the estimation of where there are targets. The second measure is the Root Mean Square Error (RMSE) of the position error. In Fig. 2 (left), the MOSPA performance, averaged over 500 Monte Carlo runs, is shown for the JPDA filter with and without resolution model, and for the case of perfect resolution, i.e., when the targets are always resolved. The results clearly show that the JPDA filter with resolution model performs better than the filter without resolution model. The performance in RMSE sense, averaged over 500 Monte Carlo runs, is shown in Fig. 2 (right). Obviously, also the RMSE performance is improved when the resolution model is incorporated in the JPDA filter. The increased RMSE of the JPDA filter in the end of the scenario is due to the fact that there is a larger probability of track switch for that filter, compared to the filter with resolution model.

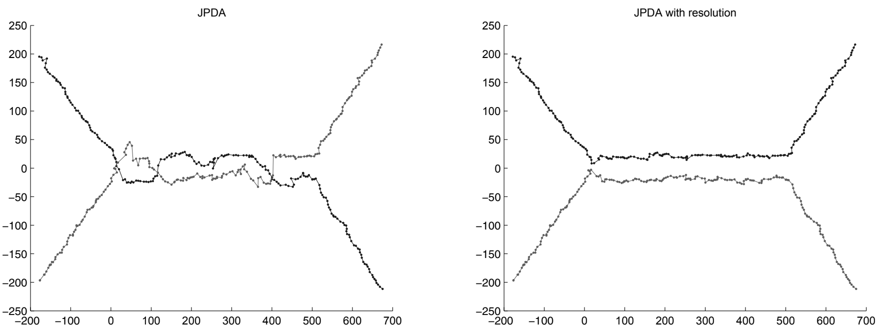

Figure 1: Typical tracking result for the JPDAF without (left) and with (right) resolution model.

6 Summary and Outlook

We have proposed a sensor resolution model for arbitrary target numbers, which is an extension of the two-target model by Koch and van Keuk [KvK97]. The resolution model leads to additional data association possibilities and to a multi-target likelihood function that takes missed detections due to merged measurements into account. As the filter update, in general, is infeasible, the extensive Gaussian mixture has been approximated by a JPDA filter. The application to a simple target tracking scenario shows a significantly improved tracking performance if the sensor resolution model is used. While these first results are encouraging, more simulations are needed to confirm the practicability of the presented approach. In particular, the stability against resolution model mismatch needs

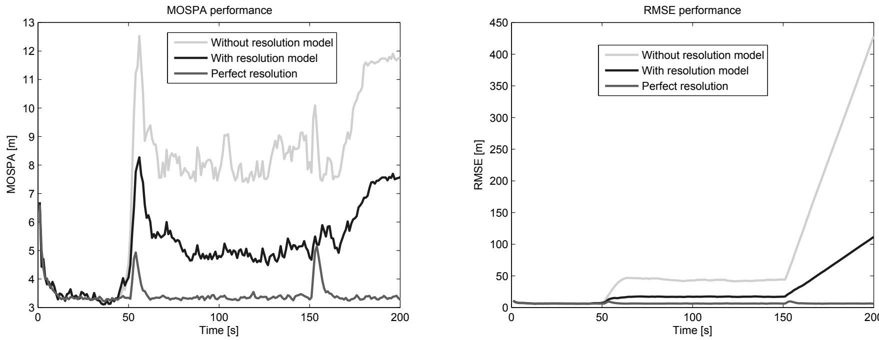

Figure 2: OPSA (left) and RMSE (right) performance of the JPDAF without resolution model (top), with resolution model (middle) in comparison to the case of perfect sensor resolution (buttom).

to be investigated. Furthermore, the resolution model and the corresponding likelihood function can also be integrated into more sophisticated tracking filters such as the Multi Hypothesis Tracker or the Probability Hypothesis Filter.

References

[BP99] Samuel Blackman and Robert Popoli. *Design and Analysis of Modern Tracking Systems*. Artech House, Norwood, MA, 1999.

[CBS84] K.C. Chang and Y. Bar-Shalom. Joint probabilistic data association with possibly unresolved measurements and maneuvers. *IEEE Transactions on Automatic Control*, 29(7):585–594, July 1984.

[DF94] F.E. Daum and R.J. Fitzgerald. Importance of resolution in multiple-target tracking. In *Signal and Data Processing of Small Targets*, volume 2235 of *Proc. SPIE*, 1994.

[FBSS83] T.E. Fortmann, Y. Bar-Shalom, and M. Scheffe. Sonar tracking of multiple targets using joint probabilistic data association. *IEEE Journal of Oceanic Engineering*, 8(3):173–183, July 1983.

[KvK97] W. Koch and G. van Keuk. Multiple hypothesis track maintenance with possibly unresolved measurements. *IEEE Transactions on Aerospace and Electronic Systems*, 33(3):883–892, July 1997.

[MCC87] Shozo Mori, K.C. Chang, and C.Y. Chong. Tracking Aircraft by Acoustic Sensors; Multiple Hypothesis Approach Applied to Possibly Unresolved Measurements. In *American Control Conference*, pages 1099–1105, June 1987.

[SUD10] D. Svensson, Martin Ulmke, and Lars Danielsson. Multitarget sensor resolution model for arbitrary target numbers. In *Signal and Data Processing of Small Targets*, volume 7698 of *Proc. SPIE*, 2010.

[SVV08] D. Schuhmacher, B.-T. Vo, and B.-N. Vo. A Consistent Metric for Performance Evaluation of Multi-Object Filters. *IEEE Transactions on Signal Processing*, 56(8):3447–3457, August 2008.