New Developments in Flexible ID Association-based Tracking Algorithm

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Abstract[1] – *For robust data association performance, tracking algorithms available in the literature utilize kinematic as well as non-kinematic information. These algorithms, however, do not provide a systematic way to utilize non-kinematic information to resolve severe and prolonged association ambiguities in the past. In a previous work, we proposed a novel framework in which kinematic and non-kinematic information of potential targets are stored as different entities, respectively denoted as tracks and IDs. The dynamic association between tracks and IDs provides the mechanism for resolving past ambiguities and reporting any remaining ambiguity to the user. However, restrictive assumptions of no false alarms and perfect detection of targets were made in our previous work. The current paper generalizes the algorithm beyond those restrictions. Moreover, algorithms for track and ID initialization and deletion are presented. Simulation results are provided to show the effectiveness of the approach.*

Keywords: Feature-aided tracking, data association, track-to-ID association, multiple-hypotheses tracking, flexible association.

1 Introduction

Data association is a crucial part of target tracking, particularly in the presence of measurement-to-track association ambiguities. Ordinarily, kinematic distances between measurements and tracks are used to obtain their association likelihoods. In situations where different targets exhibit similar kinematics, this kinematic-only discrimination approach may not yield correct associations. In such situations, if measurement data include features as well, association likelihoods computed using feature-related distances between measurements and tracks can improve the data association performance. In the tracking literature, it is shown that such an approach can significantly enhance tracking and classification performance [1,2].

Based on the non-kinematic information available to the tracker, two different processing approaches can be found in the literature: feature-aided tracking and classification-aided tracking. Feature-aided tracking (also called signature-aided tracking) uses feature information [3] and classification-aided tracking [1] uses categorical feature information. In both cases, kinematic and non-kinematic estimates (feature or class-likelihood) for each track are maintained and the information is updated as new measurements are associated with the track. Since in this type of processing all the information about targets is maintained in tracks, any track switch causes a target identity (ID) switch.

A feature-aided multiple hypothesis tracking (MHT) approach proposed by Chang and Fung [4] can defer the track association decisions until more measurement information becomes available. Thus, this approach can avoid or (at the least) acknowledge a track switch. However, in order to make it manageable, hypotheses must be pruned, thus undermining the theoretical benefits of the method. The pruning of hypotheses may even bring about a failure to resolve an ambiguity, if the period of ambiguity lasts for a long time, or if multiple pieces of information are required for resolution.

In our previous work [5] a novel framework of ID-aided tracking was presented to overcome the above-discussed limitation of the conventional tracking approaches, particularly in scenarios with severe and prolonged association ambiguities. In this framework, the tracking picture consists of tracks, IDs, and a list of global track-to-ID association hypotheses – each with a probability score. By "an ID", we mean a data structure analogous to a track, but containing only identity-related (attribute, feature, category) information, while a "track" will contain only kinematic information. An ID is created whenever a new track is confirmed. Track-to-ID associations are treated dynamically: their probabilities are either 1 or 0 at track initiation, but then are allowed to vary throughout the interval between 0 and 1 in response to track association ambiguities. In order to retain ID purity, the updating of an ID is restricted in the presence of ongoing association ambiguities. Once the period of association ambiguity is over, track-to-ID associations can be resolved if targets have distinctive features. Until then, the algorithm explicitly indicates that some ID-to-track associations have not been resolved. The ID-aided tracking approach can also be applied to kinematic-only measurement scenarios to provide users with track-to-ID association probabilities. This information can be used to determine the possible origins of a target track. Although it can acknowledge ID switches, in a kinematic-only scenario the approach will be unable to resolve IDs after the period of association ambiguity is over.

Both the ID-aided tracker and MHT maintain multiple hypotheses with dynamic probability scores. In the case of MHT, the hypotheses are complete track lists. Hence, in each iteration, multiple track-lists are required to

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be associated with measurements and updated. Meanwhile, in the case of the ID-aided tracker, the hypotheses are mapping between tracks and IDs. Only a single list of tracks is updated in each iteration. In the case of MHT, the number of hypotheses can grow unboundedly over time. In contrast, the number of hypotheses of the ID-aided tracker is bounded.

The algorithm presented in [5] was restricted by the assumptions of no false alarms and no missed detections. Moreover, very little was said about the creation of tracks and IDs, and nothing was said about their deletion. It was also assumed that the total number of confirmed tracks and the total number of IDs would always be equal. The latter assumption is inappropriate, since track deletion during a time of association ambiguity would not then be representable.

This presentation of the algorithm will generalize beyond those restrictions. In particular, the algorithm now explicitly handles false alarms and missed detections, and the number of confirmed tracks maintained at any given time can now differ from the number of IDs maintained at that time. The current version (and the version in [5]) of the ID-aided tracker can handle only feature information. Development of an ID-aided tracker based on categorical features is underway. An intermediate state of development, between [5] and the present document, appeared in [6].

The rest of the paper is organized as follows. Section 2 provides details of the ID-aided tracking algorithm. Section 3 provides simulation results and Section 4 provides concluding remarks.

2 ID-aided tracking algorithm

In this section, we present the details of the flexible ID association-based tracker, or "ID-aided tracker" for short. The algorithm predicts the global ID-to-track association hypotheses, then updates tracks, ID information and global track-to-ID association probabilities at each time step. The creation and deletion of tracks and IDs are discussed in Subsection 2.6. Until that subsection, all references to "tracks" should be read as references to "confirmed tracks".

2.1 Notations

Let $\boldsymbol{T}(k)$ denote the set of tracks, and let $\boldsymbol{C}(k)$ denote the set of IDs, at time k. (The phrase "time k" should be taken as shorthand for "the k^{th} iteration", as k is dimensionless and integer-valued.) There will always be at least as many IDs as tracks. Let $\boldsymbol{L}(k)$ denote the table of currently possible global track-to-ID association hypotheses, along with the corresponding probabilities. A global track-to-ID association hypothesis $\boldsymbol{K}$ is a set of specific hypotheses, each associating a track with an ID, subject to the constraint that each track is associated with exactly one ID and each ID is associated with at most one track. Specific hypotheses within such a global hypothesis will be denoted as (for example) K_i^t for the hypothesis that ID i is associated with track t, or K_i^0 for the hypothesis that no current track is associated with that ID.

The set of measurements up to time k is denoted Z^k, and the set of measurements at time k is denoted $\mathbf{z}(k)$. The latter set can be decomposed into a set $\mathbf{z}_{\mathrm{d}}(k)$ of kinematic measurements and a set $\mathbf{z}_{\mathrm{g}}(k)$ of feature measurements.

The probability of existence of ID i, or the total probability of associating the ID with some existing track at time k, is given by

$$p_{\text{exist}}^k(i)=\sum_{\forall t\neq 0}\sum_{\forall \boldsymbol{K}(k):\,K_i^t\in\boldsymbol{K}(k)} p\left(\boldsymbol{K}(k)\,|\,Z^k\right) \tag{1}$$

where $p\left(\boldsymbol{K}(k)\,|\,Z^k\right)$ is the probability associated with hypothesis $\boldsymbol{K}(k)$. Note that according to our formulation the existence probability of each current track is 1.

In general, detection probability depends on non-kinematic information, such as the target's radar cross section, and kinematic information, such as the target's distance from the sensor. A model is required to estimate the detection probability of a target given the kinematic and non-kinematic information available about it. Let $p_{\mathrm{D}}^k(i,t)$ denote the probability of detection of the target corresponding to the ID i at time k computed based on information up to time $k-1$, assuming that this ID corresponds to track t. Then the probability of detection of a track t at time k given the information up to time $k-1$ can be computed as

$$p_{\text{D,track}}^k(t)=\sum_{\forall i}\sum_{\forall \boldsymbol{K}(k-1):\,K_i^t\in\boldsymbol{K}(k-1)} p_{\mathrm{D}}^k(i,t)\,p\left(\boldsymbol{K}(k-1)\,|\,Z^{k-1}\right) \tag{2}$$

Similarly, the probability of detection of an ID i is given by

$$p_{\text{D,ID}}^k(i)=\sum_{\forall t\neq 0}\sum_{\forall \boldsymbol{K}(k-1):\,K_i^t\in\boldsymbol{K}(k-1)} p_{\mathrm{D}}^k(i,t)\,p\left(\boldsymbol{K}(k-1)\,|\,Z^{k-1}\right) \tag{3}$$

Since track 0 denotes the absence of a track, it is excluded from the above summation.

Let λ_{FA} denote the expected number of false alarms (and/or new targets) at each iteration. Note that all the measurements belonging to a given iteration are assumed to come from a single sensor.

In order to process the set $\mathbf{z}(k)$ of measurements at each iteration, the global measurement-to-track hypotheses and global measurement-to-ID hypotheses will have to be considered. A global measurement-to-ID hypothesis $\boldsymbol{I}$ is a set of specific hypotheses, each associating a measurement with an ID, such that at most one ID is associated with each measurement and at most one measurement is associated with each ID. Specific hypotheses within such a global hypothesis will be denoted as (for example) I_b^j for the hypothesis that measurement j originated from the target corresponding to ID b, or I_b^0 for the hypothesis that no measurements originated from that ID. Similarly, a global measurement-to-track hypothesis $\boldsymbol{J}$ is a set of specific hypotheses, each associating a measurement with a track, such that at most one track is associated with each measurement and at most one measurement is associated with each track.

Let $\delta_{\boldsymbol{I}}(j)$ be equal to either 0 or 1, depending on whether the j^{th} ID is associated with a measurement or not, according to the hypothesis $\boldsymbol{I}$ – that is, 1 if that ID is associated with a measurement and 0 if it is not. Let $\phi(\boldsymbol{I})$ be the number of false alarms or new targets implied by $\boldsymbol{I}$ (i.e., the number of measurements not associated with any ID according to $\boldsymbol{I}$) and let $\mu(\boldsymbol{I})$ be the number of missed detections implied by $\boldsymbol{I}$ (i.e. the number of IDs not associated with any measurement according to $\boldsymbol{I}$). Note that the difference $\phi(\boldsymbol{I})$ - $\mu(\boldsymbol{I})$ will be equal for all global hypotheses $\boldsymbol{I}$ pertaining to a given set $\mathbf{z}(k)$ of measurements.

Similarly, let $\delta_{\boldsymbol{J}}(j)$ be equal to either 0 or 1, depending on whether the j^{th} track is associated with a measurement or not, according to $\boldsymbol{J}$. The quantities $\phi(\boldsymbol{J})$ and $\mu(\boldsymbol{J})$ are also defined in a similar manner for global measurement-to-track hypotheses as they are for global measurement-to-ID hypotheses, but now referring to tracks instead of IDs.

2.2 Predicting the global track-to-ID association hypotheses

As introduced in Section 2.1, let $p(\boldsymbol{K}(k)\,|\,Z^k)$ be the probability for the global track-to-ID hypothesis $\boldsymbol{K}$ according to the table $\boldsymbol{L}(k)$. In section 2.5, the probabilities $p(\boldsymbol{K}(k)\,|\,Z^k)$ will be derived from the probabilities from the previous iteration, i.e. $p(\boldsymbol{K}(k-1)\,|\,Z^{k-1})$. But in order to get there, we will need the projected probabilities $p(\boldsymbol{K}(k)\,|\,Z^{k-1})$. These projected probabilities will also be used in the update procedures for the tracks and the IDs. We have

$$p(\boldsymbol{K}(k)\,|\,Z^{k-1}) = \sum_{\forall \boldsymbol{K}'} p(\boldsymbol{K}(k)\,|\,\boldsymbol{K}'(k-1))\,p(\boldsymbol{K}'(k-1)\,|\,Z^{k-1}) \tag{4}$$

where we approximate $p(\boldsymbol{K}(k)\,|\,\boldsymbol{K}'(k-1))$ according to the amount of kinematic overlap among the tracks, as follows. If the hypothesis $\boldsymbol{K}$ leaves unassociated an ID that is associated with a track according to the hypothesis $\boldsymbol{K}'$, or vice-versa, then $p(\boldsymbol{K}(k)\,|\,\boldsymbol{K}'(k-1)) = 0$. Otherwise, let $\lambda(t,t')$ denote the likelihood density for track t to be measured at the predicted position of track t' (assuming successful detection). That is, if track t has a predicted state estimate $\mathbf{x}_t(k\,|\,k-1)$ and a predicted covariance matrix $\mathbf{P}_t(k\,|\,k-1)$, then we let $\lambda(t,t')$ be the value taken by a Gaussian probability distribution function having that covariance and centred on that state estimate, restricted to the measured (position) dimensions, evaluated at the position of the predicted state estimate of track t' (i.e., at the position $H\mathbf{x}_{t'}(k\,|\,k-1)$, where H is the measurement matrix). Now

$$p(\boldsymbol{K}(k)\,|\,\boldsymbol{K}'(k-1)) \propto \prod_{\forall l} \lambda(t_l, t'_l) \tag{5}$$

then normalized so that $\sum_{\forall \boldsymbol{K}} p(\boldsymbol{K}(k)\,|\,\boldsymbol{K}'(k-1)) = 1$, where t_l and t'_l denote the tracks that are associated with ID l according to hypotheses $\boldsymbol{K}$ and $\boldsymbol{K}'$ respectively. The IDs included in the product, in equation (5), are only those with which a track is associated according to the hypotheses $\boldsymbol{K}$ and $\boldsymbol{K}'$.

2.3 Updating the IDs

The probability of the specific measurement-to-ID association hypothesis I_b^j is given by

$$p(I_b^j\,|\,Z^k) = \sum_{\forall \boldsymbol{I}:I_b^j \in \boldsymbol{I}} p(\boldsymbol{I}\,|\,Z^k) \tag{6}$$

where the probability for the global measurement-to-ID hypothesis $\boldsymbol{I}$ is given by

$$\begin{aligned} p(\boldsymbol{I}\,|\,Z^k) \propto{}& \frac{\lambda_{\text{FA}}^{\phi(\boldsymbol{I})} e^{-\lambda_{\text{FA}}}}{\phi(\boldsymbol{I})!}\, p(\mathbf{z}(k)\,|\,\boldsymbol{I}, Z^{k-1}) \\ &\times \left(\prod_{\forall i} \left(p_{\text{D,ID}}^k(i)\delta_{\boldsymbol{I}}(i) + \left(1 - p_{\text{D,ID}}^k(i)\right)\left(1 - \delta_{\boldsymbol{I}}(i)\right)\right)\right) \end{aligned} \tag{7}$$

then normalized so that $\sum_{\forall \boldsymbol{I}} p(\boldsymbol{I}\,|\,Z^k) = 1$. $p_{\text{D,ID}}^k(i)$ is defined in (3). In deriving (7) we assume a Poisson distribution for the false alarms and/or new targets. Note that j can be zero in equation (6), in which case we are referring to the probability that no measurements are associated with the target corresponding to ID b. If we assume that the probability of detection is equal for all targets, then equation (7) reduces to

$$\begin{aligned} p(\boldsymbol{I}\,|\,Z^k) \propto{}& \frac{\lambda_{\text{FA}}^{\phi(\boldsymbol{I})} e^{-\lambda_{\text{FA}}}}{\phi(\boldsymbol{I})!}\, p_{\text{D}}^{\,n(k)-\mu(\boldsymbol{I})} \left(1 - p_{\text{D}}\right)^{\mu(\boldsymbol{I})} \\ &\times p(\mathbf{z}(k)\,|\,\boldsymbol{I}, Z^{k-1}) \end{aligned} \tag{8}$$

where $n(k)$ is the number of IDs being considered at time k (that is, the number of IDs in the system after time k-1).

The final term of equation (8) is given by

$$p(\mathbf{z}(k)\,|\,\boldsymbol{I}, Z^{k-1}) = \sum_{\forall \boldsymbol{J}} p(\mathbf{z}(k)\,|\,\boldsymbol{I}, \boldsymbol{J}, Z^{k-1})\,p(\boldsymbol{J}\,|\,\boldsymbol{I}, Z^{k-1}) \tag{9}$$

where $p(\boldsymbol{J}\,|\,\boldsymbol{I}, Z^{k-1})$ is equal to the sum of the probabilities $p(\boldsymbol{K}(k)\,|\,Z^{k-1})$ over all global track-to-ID hypotheses $\boldsymbol{K}(k)$ that are compatible with $\boldsymbol{I}$ and $\boldsymbol{J}$ together. The probability density $p(\mathbf{z}(k)\,|\,\boldsymbol{I}, \boldsymbol{J}, Z^{k-1})$ is approximated as a product of probability densities dictated by the existing tracks and IDs. By decomposing $\mathbf{z}(k)$ into kinematic measurements and feature measurements, we can express it as

$$\begin{aligned} p(\mathbf{z}(k)\,|\,\boldsymbol{I}, \boldsymbol{J}, Z^{k-1}) ={}& p(\mathbf{z}_{\text{d}}(k)\,|\,\boldsymbol{J}, \boldsymbol{T}(k-1)) \\ &\times p(\mathbf{z}_{\text{g}}(k)\,|\,\boldsymbol{I}, \boldsymbol{C}(k-1)) \end{aligned} \tag{10}$$

Now $p(\mathbf{z}_{\text{d}}(k)\,|\,\boldsymbol{J}, \boldsymbol{T}(k-1))$ is itself a product of probability densities. If we denote the m^{th} kinematic measurement in $\mathbf{z}_{\text{d}}(k)$ as $\mathbf{z}_{\text{d}}^{(m)}(k)$, then

$$p(\mathbf{z}_{\text{d}}(k)\,|\,\boldsymbol{J}, \boldsymbol{T}(k-1)) = \prod_{\forall m} p(\mathbf{z}_{\text{d}}^{(m)}(k)\,|\,\boldsymbol{J}, \boldsymbol{T}(k-1)) \tag{11}$$

If the hypothesis $\boldsymbol{J}$ associates $\mathbf{z}_{\text{d}}^{(m)}(k)$ with an existing track of $\boldsymbol{T}(k-1)$, then we compute $p(\mathbf{z}_{\text{d}}^{(m)}(k)\,|\,\boldsymbol{J}, \boldsymbol{T}(k-1))$ by evaluating a Gaussian probability density function, given by that track's state estimate and covariance matrix (and restricted to the measured dimensions), at the position of the measurement. Otherwise, $p\left(\mathbf{z}_{\mathrm{d}}^{(m)}(k)\,|\,\boldsymbol{J},\boldsymbol{T}(k-1)\right)=1/V_{\mathrm{d}}$, where V_{d} is the total volume of the region of interest (restricted to the measured dimensions).

Similarly,

$$p\left(\mathbf{z}_{\mathrm{g}}(k)\,|\,\boldsymbol{I},\boldsymbol{C}(k-1)\right)=\prod_{\forall m} p\left(\mathbf{z}_{\mathrm{g}}^{(m)}(k)\,|\,\boldsymbol{I},\boldsymbol{C}(k-1)\right) \qquad (12)$$

where $\mathbf{z}_{\mathrm{g}}^{(m)}(k)$ is the m^{th} feature measurement in $\mathbf{z}_{\mathrm{g}}(k)$. How to proceed from here depends on the way in which ID-related data are represented. So far, all work on the ID-aided tracking algorithm has treated targets as having a true value in an abstract Euclidean "feature space", and has treated all feature measurements as independent estimates of that true value. The ID data structure, then, consists of a feature space estimate and a corresponding covariance matrix. Evaluation of $p\left(\mathbf{z}_{\mathrm{g}}^{(m)}(k)\,|\,\boldsymbol{I},\boldsymbol{C}(k-1)\right)$ is then analogous to evaluation of $p\left(\mathbf{z}_{\mathrm{d}}^{(m)}(k)\,|\,\boldsymbol{J},\boldsymbol{T}(k-1)\right)$: If the hypothesis $\boldsymbol{I}$ associates $\mathbf{z}_{\mathrm{g}}^{(m)}(k)$ with an existing ID from $\boldsymbol{C}(k-1)$, then $p\left(\mathbf{z}_{\mathrm{g}}^{(m)}(k)\,|\,\boldsymbol{I},\boldsymbol{C}(k-1)\right)$ is given by evaluating a Gaussian probability distribution function, given by the ID's state estimate and covariance matrix (and restricted to the measured dimensions), at the "position" (in feature space) of the measurement. Otherwise $p\left(\mathbf{z}_{\mathrm{g}}^{(m)}(k)\,|\,\boldsymbol{I},\boldsymbol{C}(k-1)\right)=1/V_{\mathrm{g}}$, where V_{g} is the total volume of the feature space (restricted to the measured dimensions).

Alternative calculations of $p\left(\mathbf{z}_{\mathrm{g}}^{(m)}(k)\,|\,\boldsymbol{I},\boldsymbol{C}(k-1)\right)$ are possible, based on different models of the space of possible feature values or classifications.

Each ID is updated by only one feature measurement: that for which the probability $p\left(I_b^j\,|\,Z^k\right)$ is greatest. If $p\left(I_b^j\,|\,Z^k\right)< p\left(I_b^0\,|\,Z^k\right)$ for all $j > 0$, the ID is not updated at all. Given the way IDs have been represented in this work so far, this update procedure is merely the standard procedure for sequential estimation of a constant vector using observations which are perturbed by additive Gaussian noise. This is equivalent to a Kalman Filter in the case of a stationary process model and no process noise. However, we make one modification to this procedure for the sake of caution (in order to avoid contamination among the IDs): For each ID, the specific hypothesis probabilities $p\left(I_b^j\,|\,Z^k\right)$ are sorted in decreasing order, $\{p_1, p_2, \ldots\}$. Before applying the update to the feature estimate, the measurement covariance is inflated by the factor $1/(p_1-p_2)$. The detailed procedure is provided in [5]. This seemingly *ad hoc* factor is based on finding the q-least committed [7] set of basic belief assignments among all possible sets from which our specific hypothesis probabilities could be derived, and weighting the measurement by an amount equal to the weight of the belief assignment that applies to that measurement alone.

The most conspicuous gap in the development of ID-aided tracking is in the description of the IDs. Treating an ID as an estimate of a point in feature space is surely an inadequate approach for a real, practical system. We might instead treat an ID as a set of belief assignments, in the sense of Dempster-Shafer theory, but in that case further work is required to find an appropriate way to compute the quantity $p\left(\mathbf{z}_{\mathrm{g}}^{(m)}(k)\,|\,\boldsymbol{I},\boldsymbol{C}(k-1)\right)$ in equation (12).

2.4 Updating the tracks

The probability for the global measurement-to-track hypothesis $\boldsymbol{J}$ is given by

$$\begin{aligned} p\left(\boldsymbol{J}\,|\,Z^k\right) &\propto \frac{\lambda_{\mathrm{FA}}^{\phi(\boldsymbol{J})}e^{-\lambda_{\mathrm{FA}}}}{\phi(\boldsymbol{J})!}\, p\left(\mathbf{z}(k)\,|\,\boldsymbol{J},Z^{k-1}\right) \\ &\times\left(\prod_{\forall t}\left(p_{\mathrm{D,track}}^{k}(t)\delta_{\boldsymbol{J}}(t)+\left(1-p_{\mathrm{D,track}}^{k}(t)\right)\left(1-\delta_{\boldsymbol{J}}(t)\right)\right)\right) \end{aligned} \qquad (13)$$

then normalized so that $\sum_{\forall \boldsymbol{J}} p\left(\boldsymbol{J}\,|\,Z^k\right)=1$. $p_{\mathrm{D,track}}^{k}(t)$ is defined in (2). If we assume that the probability of detection is equal for all targets, then equation (13) reduces to

$$\begin{aligned} p\left(\boldsymbol{J}\,|\,Z^k\right) &\propto \frac{\lambda_{\mathrm{FA}}^{\phi(\boldsymbol{J})}e^{-\lambda_{\mathrm{FA}}}}{\phi(\boldsymbol{J})!}\, p_{\mathrm{D}}^{\,n(k)-\mu(\boldsymbol{J})}\left(1-p_{\mathrm{D}}\right)^{\mu(\boldsymbol{J})} \\ &\times p\left(\mathbf{z}(k)\,|\,\boldsymbol{J},Z^{k-1}\right) \end{aligned} \qquad (14)$$

where in this case $n(k)$ is the number of tracks (not IDs) being considered at time k.

The final term of equation (14) is given by

$$p\left(\mathbf{z}(k)\,|\,\boldsymbol{J},Z^{k-1}\right)=\sum_{\forall \boldsymbol{I}} p\left(\mathbf{z}(k)\,|\,\boldsymbol{I},\boldsymbol{J},Z^{k-1}\right)p\left(\boldsymbol{I}\,|\,\boldsymbol{J},Z^{k-1}\right) \qquad (15)$$

where $p\left(\boldsymbol{I}\,|\,\boldsymbol{J},Z^{k-1}\right)$ is equal to $p\left(\boldsymbol{J}\,|\,\boldsymbol{I},Z^{k-1}\right)$ (see previous section). The probability density $p\left(\mathbf{z}(k)\,|\,\boldsymbol{I},\boldsymbol{J},Z^{k-1}\right)$ was discussed in the previous section.

Having found the hypothesis probabilities, the tracks can be updated according to a Kalman Filter, with each track using the measurement that is associated with it according to the single best global measurement-to-track association hypothesis. Alternatively, the tracks could be updated by a weighted average of hypotheses, as in the Probabilistic Data Association Filter (PDAF) [8].

2.5 Updating the global track-to-ID association hypothesis probabilities

The global track-to-ID association hypothesis probabilities are given by

$$p\left(\boldsymbol{K}(k)\,|\,Z^k\right)\propto p\left(\mathbf{z}(k)\,|\,\boldsymbol{K}(k),Z^{k-1}\right)p\left(\boldsymbol{K}(k)\,|\,Z^{k-1}\right) \qquad (16)$$

then normalized so that $\sum_{\forall \boldsymbol{K}} p\left(\boldsymbol{K}(k)\,|\,Z^k\right)=1$. See section 2.2 for $p\left(\boldsymbol{K}(k)\,|\,Z^{k-1}\right)$.

The term $p\left(\mathbf{z}(k)\,|\,\boldsymbol{K}(k),Z^{k-1}\right)$ is given by

$$\begin{aligned} &p\left(\mathbf{z}(k)\,|\,\boldsymbol{K}(k),Z^{k-1}\right) \\ &\quad=\sum_{\forall \boldsymbol{I}}\sum_{\forall \boldsymbol{J}} p\left(\mathbf{z}(k)\,|\,\boldsymbol{I},\boldsymbol{J},Z^{k-1}\right)p\left(\boldsymbol{I},\boldsymbol{J}\,|\,\boldsymbol{K}(k),Z^{k-1}\right) \end{aligned} \qquad (17)$$

where $p\left(\mathbf{z}(k)\,|\,\boldsymbol{I},\boldsymbol{J},Z^{k-1}\right)$ was dealt with in section 2.3.

Note that the hypothesis $\boldsymbol{J}$ is determined, given $\boldsymbol{I}$ and $\boldsymbol{K}(k)$, because a measurement is associated with a given track if and only if it is also associated with the ID that is associated with that track. Thus, the probability

$p(\boldsymbol{I},\boldsymbol{J}\,|\,\boldsymbol{K}(k),Z^{k-1})$ in equation (17) is zero if the hypotheses $\boldsymbol{I}$ and $\boldsymbol{J}$ together disagree with $\boldsymbol{K}(k)$. Otherwise, it can be expressed as:

$$p(\boldsymbol{I},\boldsymbol{J}\,|\,\boldsymbol{K}(k),Z^{k-1}) = C\frac{\lambda_{\mathrm{FA}}{}^{\phi(\boldsymbol{J})}e^{-\lambda_{\mathrm{FA}}}}{\phi(\boldsymbol{J})!} \times\left(\prod_{\forall t}\left(p_{\mathrm{D}}^{k}(i(t),t)\delta_{\boldsymbol{J}}(t)+\left(1-p_{\mathrm{D}}^{k}(i(t),t)\right)\left(1-\delta_{\boldsymbol{J}}(t)\right)\right)\right) \quad (18)$$

where C is a constant that will cancel itself out in the normalization of equation (16), $i(t)$ is the index of the ID with which track t is associated according to $\boldsymbol{K}$, and $p_{\mathrm{D}}^{k}(i,t)$ is as described in subsection 2.1. If all detection probabilities are equal, equation (18) can be written as follows, with $n(k)$ being interpreted as in equation (14):

$$p(\boldsymbol{I},\boldsymbol{J}\,|\,\boldsymbol{K}(k),Z^{k-1}) = C\frac{\lambda_{\mathrm{FA}}{}^{\phi(\boldsymbol{J})}e^{-\lambda_{\mathrm{FA}}}}{\phi(\boldsymbol{J})!}\,p_{\mathrm{D}}{}^{n(k)-\mu(\boldsymbol{J})}(1-p_{\mathrm{D}})^{\mu(\boldsymbol{J})} \quad (19)$$

2.6 Creation and deletion of tracks and IDs

The ID-aided tracker keeps two sets of tracks known as confirmed tracks and initial tracks. The life-cycle of each track begins as an initial track.

At each time step the measurements are first associated with confirmed tracks and the unassociated measurements are then associated with initial tracks. Measurements (contacts) that do not contribute to the updating of an existing confirmed or initial tracks – or, in the case of a PDAF-like track update method, have a very small weight (less than some pre-set threshold) for the updating of some existing track – are used to create initial tracks. Each initial track is started using one unassociated measurement each from two consecutive time steps, if these measurements satisfy velocity gating condition. No ID is associated with the initial tracks.

The initial tracks are associated with new measurements based on their kinematic information only. Measurement gating is performed to make sure only possible measurements are considered for each track. If an initial track is not associated with a measurement for more than some predefined number of consecutive iterations, the initial track is deleted. If an initial track gets associated with some predefined number of measurements, the track is confirmed and an ID is generated based on the feature information of the measurements that were associated with the initial track. If the measurements have no ID-relevant content, the new ID is null valued. This new track and this new ID are associated with each other, so every hypothesis in the table ***L(k)*** is extended to express this link.

A confirmed track is deleted if it is not updated after some pre-set number of consecutive iterations. Every hypothesis in the table ***L(k)*** is then modified so that an ID which was associated with the now-deleted track is left unassociated.

An ID is deleted if its “probability of existence”, as given in equation (1), drops below some pre-set threshold, and stays there for some pre-set number of consecutive iterations. The hypotheses that associate the now-deleted ID with a track are all deleted, while the remaining hypotheses are re-normalized (and modified to remove references to the now-deleted ID).

3 Simulation Results

Simulation results are presented based a single-sensor two-target scenario. Figure 1 shows the sensor’s position and its surveillance region, and the trajectories of the two targets. The targets start well separated and move towards each other. At about 1.5km from each other, each target performs its first maneuver, a coordinated turn with a turn rate of 3 degrees/min. The targets move in parallel for 75 km, which is about one-third of the length of their total path, keeping a distance of 1.5 km between them. After that, each target performs its second maneuver (a coordinated turn at the same turn rate as the first maneuver) and the targets move away from each other. Tracking algorithms face severe association ambiguity for a prolonged interval during the time in which the targets move in parallel. The speed of each target is 25 m/sec.

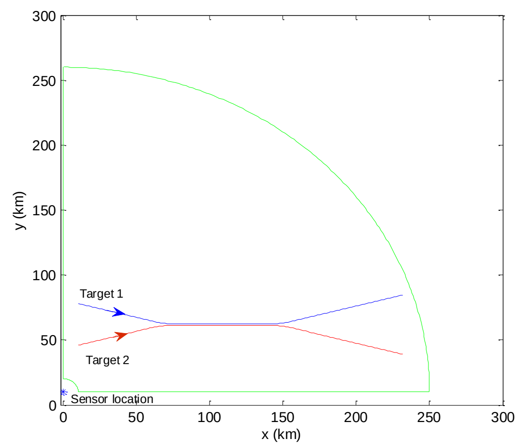

Figure 1: Sensor surveillance region and target trajectories in the simulation scenario.

The sensor measures range, azimuth and ID features of the targets. The range measurement error standard deviation is 100m and the azimuth measurement error standard deviation is 0.01 radian (or 0.57 degree). The features simulated in this work are generic; no specific physical quantity is being modeled. Hence, the features are simply labeled as “feature 1” and “feature 2”. The feature measurement error covariance matrix is equal to the identity matrix. In order to analyze the sensitivity of the performance of the ID-aided tracker to different values of false alarm rate and probability of detection (p_{D}), a number of simulations are performed.

Figures 2 and 3 show the kinematic measurements and feature measurements in a typical run of the scenario. Figure 2 shows overlap between measurements when targets move in parallel formation. Figure 3 shows the feature measurements. In both figures, measurements originating from target 1, target 2 and false alarms are shown in blue, red and green, respectively. The overlap between the target-originated kinematic measurements (when the targets are moving in parallel) and feature measurements give some indication of the level of difficulty faced in distinguishing the targets from each other.

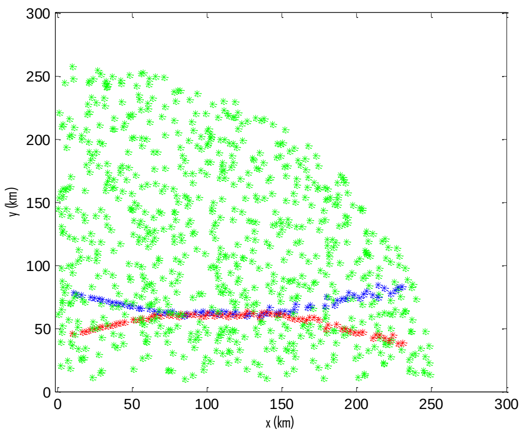

Figure 2: Kinematic measurements in a typical run with λ_{FA} = 10 and p_D = 0.9. Blue and red respectively indicate targets 1 and 2, while false alarms are green.

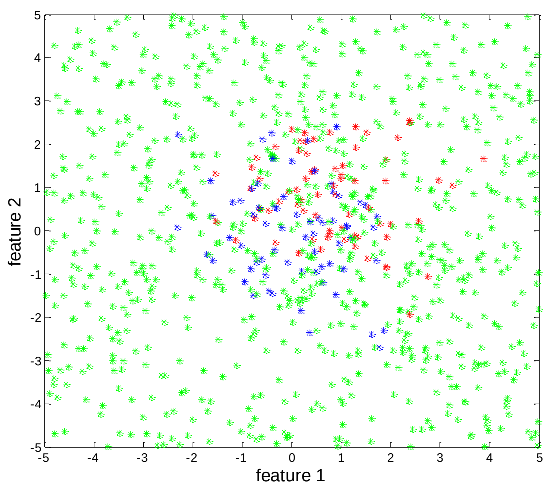

Figure 3: Feature measurements in a typical run with λ_{FA} = 10 and p_D = 0.9. Blue and red respectively indicate targets 1 and 2, while false alarms are green.

In this work, a feature-aided 2-D association algorithm (making firm assignments at each iteration) is also implemented, in order to serve as a baseline for comparing the performance of ID-aided tracking. Both trackers use a Kalman filter and assume a discrete white noise acceleration model [9] with process noise of 0.2 m/s^2. Figures 4 and 5 show the tracks obtained by ID-aided tracking and feature-aided tracking in a typical run of scenario with false alarm rate of 10 and probability of detection set at 0.9. In the case of the feature-aided tracker (Figure 5) the association ambiguity causes an ID switch. However, the ID-aided tracker could correctly assign the ID to the tracks after the association ambiguity event is over (Figure 4). Note that in the case of ID-aided tracker, the color of each track is based on the ID with which the track is most strongly associated. Hence, colors of tracks change when there is a switch in ID association.

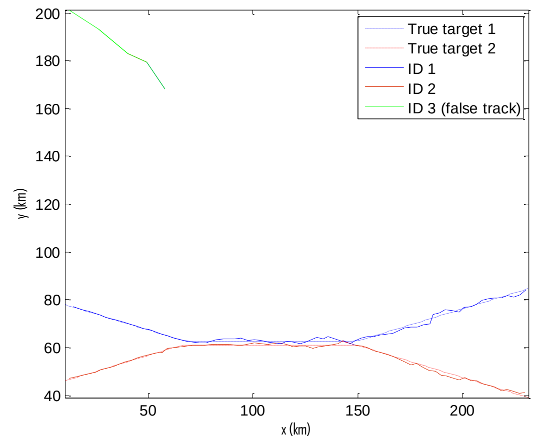

Figure 4: Tracks from ID-aided tracking algorithm in a typical Monte Carlo run (λ_{FA} = 10 and p_D = 0.9).

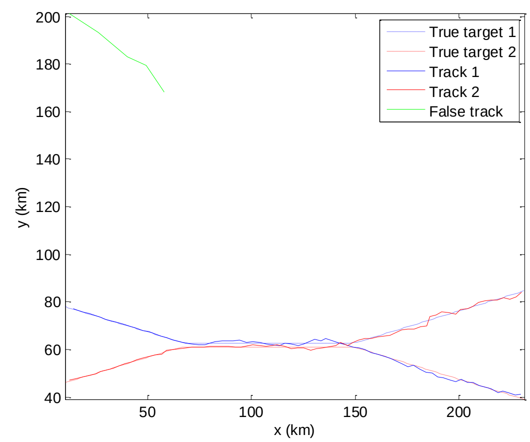

Figure 5: Tracks from feature-aided tracker in a typical Monte Carlo run (λ_{FA} = 10 and p_D = 0.9).

Table 1 shows the track and ID consistency performance when the two tracking algorithms are applied to the scenario with and without false alarm and missed detections. For the feature-aided tracker, each track represents an ID, so a track switch is equivalent to an ID switch. In the case of the ID-aided tracker, IDs are separate entities from tracks. To analyze the performance of the algorithms at each measurement time, tracks are associated with true targets according to a single-track-to-single-target association criterion, based on the proximity of each track to the true targets. As a result of this track-to-target association, different segments of track may be connected to different true targets. In the case of the feature-aided tracker, a track-switch is declared if different tracks are associated with a target before and after it passes through an ambiguity region.

In the case of the ID-aided tracker, for each true target we find the ID with which this target is associated until there is an association ambiguity. The IDs are the ones associated with track segments which are, in turn, associated with a particular true target based on track-to-target association at that point. Once the ID-to-track association ambiguity is over – i.e., an ID is again firmly (with probability greater than $1\text{-}10^{-4}$) associated with a track and hence with a true target via track-to-target association – we check whether this ID is the same as the previously associated ID for the same true target. If the answer is negative, we declare an ID switch. In addition, the percentage of time during which ambiguous IDs are associated with tracks is computed. The cases in which ambiguity is not resolved even at track termination are also noted.

Table 1: Track and ID consistency performance over 1000 runs.

Performance metric	False alarm rate 0, PD 1		False alarm rate 10, PD 0.9	
	Feature-aided tracking	ID-aided tracking	Feature-aided tracking	ID-aided tracking
Track switch percentage	16.5%	0%	26.0%	0.6%
Percentage of track-life with ambiguous ID	0%	39.4%	0%	40.1%
Unresolved ID association at track termination	0%	0.1%	0%	0.2%
Track loss	0%	0%	3.9%	0.9%
# of False tracks per run	0	0	0.15	0.15

The ID-aided tracker outperforms the feature-aided tracker in terms of ID consistency. It can be seen that the feature-aided tracker suffers an ID switch in about 16.5% of the runs in the case of a clean environment (no false alarms and no missed detections), and 26.0% of the runs in the presence of false alarms and missed detections. On the other hand, the ID-aided tracking algorithm suffers an ID switch in only 0.6% of the runs in the presence of false alarms and missed detections and no ID switch in their absence.

In the case of the ID-aided tracker, tracks have ambiguous ID association during (on average) 39.4% of their life-times in the clean environment. This result is due to the fact that association ambiguity persists through nearly 35% of each track's life. Another 5% of track life is needed on average to completely resolve the ID-to-track associations. In addition, for 1 out of the 1000 runs, the ID-aided tracker could not resolve the IDs before the termination of the corresponding tracks. In the presence of false alarms and missed detections, the tracks have ambiguous ID for slightly longer time on average and in 2 out of 1000 runs IDs could not be resolved. When the assignment–based algorithms are used, by construct tracks are always unambiguously connected with IDs.

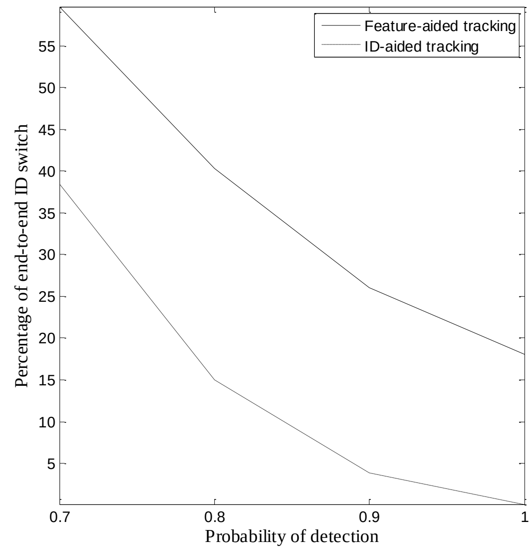

Figure 6: Percentage of ID switch for different values of p_D and average false alarms per scan equal to 10.

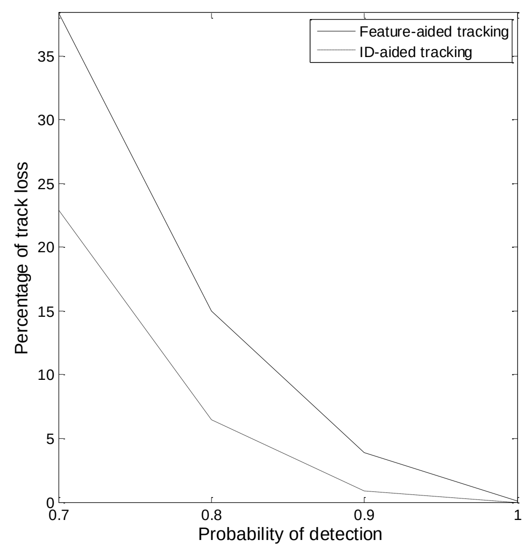

Figure 7: Track loss percentage for different values of p_D and average false alarms per scan equal to 10.

In addition, Table 1 shows the percentage of track loss cases averaged over 1000 runs. It can be noted that track loss is considerably lower in the case of the ID-aided tracker which considers the possibility of a track switch while using features to make association decisions. In contrast, when the feature-aided tracker suffers a track switch, the kinematic- and feature-based information may not agree on which measurement to associate a track with. This conflict is the cause of the higher track loss rate in the case of the feature-aided tracker. The two trackers generate about the same number of false tracks. The trackers perform about the same in estimating the kinematic state of the targets. For this reason the corresponding results are not presented here.

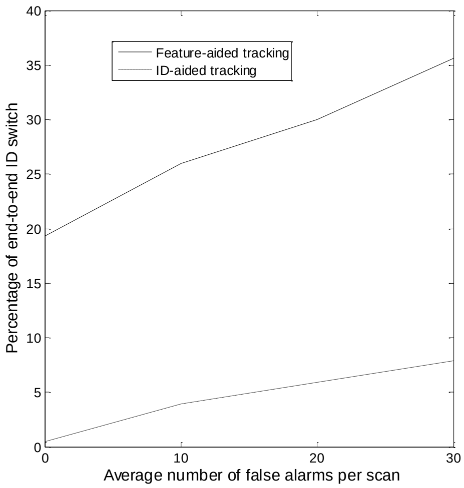

Figure 8: Percentage of ID switch for different values of average false alarms per scan and p_D equal to 0.9.

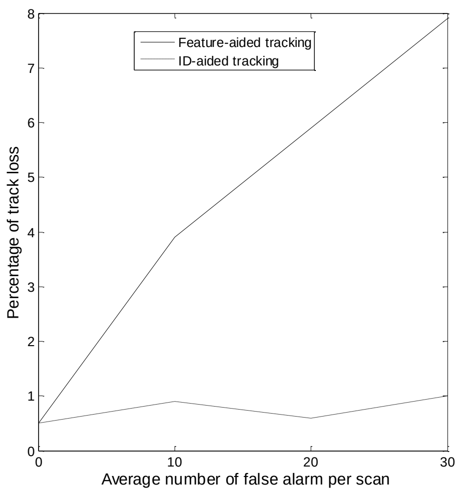

Figure 9: Track loss percentage for different values of average false alarms per scan and p_D equal to 0.9.

Figure 6 compares the performance of ID-aided tracking and feature-aided tracking in terms of the percentage of ID switch events for different values of p_D. The false alarm rate per scan is equal to 10 for these simulations. 1000 Monte Carlo runs are performed to obtain each result. As expected, for both trackers, end-to-end track switch increases as probability of detection is decreased. It can be also seen that the performance of ID-aided tracker is always better.

Figure 7 compares the performance of the two trackers for track loss percentage. The false alarm rate is fixed at 10 in these simulations. Again, each result is based on 1000 Monte Carlo runs. The ID-aided tracker consistently outperforms the feature-aided tracker.

Figures 8 and 9 show the performance of the two trackers for different values of the average number of false alarms per scan. Each result is based on 1000 Monte Carlo runs and in each case the PD is equal to 0.9. It can be seen that ID-aided tracker performs significantly better than the feature-aided tracker in terms of ID switch and track loss.

4 Conclusions

In this work, we present an updated ID-aided tracking framework that provides a systematic approach for using non-kinematic information to resolve severe and prolonged data association ambiguities in the presence of false alarms and missed detections. Simulation results show that the algorithm outperforms a feature-aided 2D assignment tracker in terms of consistency of target ID and track loss for different values of p_D and false alarm rate.

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