Multisensor Track-to-Track Association for Tracks with Dependent Errors

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The problem of track-to-track association has been considered until recently in the literature only for pairwise associations. In view of the extensive recent interest in multisensor data fusion, the need to associate simultaneously multiple tracks has arisen. This is due primarily to bandwidth constraints in real systems, where it is not feasible to transmit detailed measurement information to a fusion center but, in many cases, only local tracks. As it has been known in the literature, tracks of the same target obtained from independent sensors are still dependent due to the common process noise [2]. This paper derives the exact likelihood function for the track-to-track association problem from multiple sources, which forms the basis for the cost function used in a multidimensional assignment algorithm that can solve such a large scale problem where many sensors track many targets. While a recent work [14] derived the likelihood function under the assumption that the track errors are independent, the present paper incorporates the (unavoidable) dependence of these errors.

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1. INTRODUCTION

In this paper we consider the problem of associating tracks represented by their local estimates and covariances from S sources. These sources are processors that use data from corresponding local sensor systems. While different sensors have, typically, independent measurement errors, the local state estimation errors for the same target will be dependent due to the common prior or process noise. This dependence is characterized by the crosscovariances of the local estimation errors—see [2], Sec. 8.4. The association presented in [2], while accounting for the crosscovariances of the track errors, is limited to pairs of tracks, i.e., it is suitable for the situation of two lists (sources) of tracks. Consequently, if this is used when there are more than two lists of local tracks, the results will depend on the order in which the lists are considered. This order-dependence can be avoided only by simultaneous consideration of all S-tuples when there are S lists.

While a recent work [14] derived the likelihood function under the assumption that the state estimation errors are independent, the present paper incorporates the (unavoidable) dependence of these errors. Earlier work on fusion of multiple tracks can be found in [13]. This work also addressed the issue of dependence among tracks due to prior communication. The general fusion of crosscorrelated tracks was derived in [11]. A recent comparison of different fusion techniques can be found in [15].

The goal of this paper is to derive a likelihood-ratio based cost function suitable for the use of a multidimensional assignment (S-D, see, e.g., [3], Ch. 2) to decide which tracks should be fused. The cost function should allow simultaneous consideration of S tracks corresponding to the same target (one from each source) or any subset of this.

First we shall derive the likelihood function of the hypothesis that S tracks are from the same target, i.e., that they have a common origin. This derivation is based on [17] where it was presented for the purpose of sensor bias estimation for $S = 2$ sensors and it accounted for the dependence of the track estimation errors across sensors. More recently [14] developed the likelihood function for the association of tracks from an arbitrary number of sensors, but under the assumption that their track (local state estimation) errors are independent. This assumption, however, is not satisfied when the target state equations have process noise which is necessary to model motion uncertainty.

These likelihood functions are, however, not dimensionless since they are joint pdfs (probability density functions) of state vectors. As indicated in [4], Sec. 1.4.2, the pdf of a vector consisting of position and velocity in an n-dimensional Cartesian space has its physical dimension given by the inverse of the product of the physical dimensions of its components, i.e., $(\text{length})^{-n} \cdot (\text{length/time})^{-n}$. Consequently, the joint pdf of S such vectors has physical dimension of $(\text{length})^{-2Sn} \cdot (\text{time})^{Sn}$. Therefore, one cannot compare the likelihood functions of the hypothesis that S tracks have a common origin with the hypothesis that, say, a subset of them, consisting of $M < S$ tracks, have a common origin, i.e, one has an incompatibility. The remedy for this incompatibility problem is to use dimensionless likelihood ratios obtained by dividing a common-origin likelihood function with the likelihood function of the hypothesis that these tracks are all of different origin. The latter likelihood function will consist of a diffuse pdf (a uniform distribution in the augmented (product) state space—see [4], Sec. 2.3.4), as detailed later. Using these likelihood ratios one can compare all the hypotheses regardless of how many tracks of common origin are assumed in them.

The methodology of this paper, based on likelihood ratios and a diffuse prior for the target state estimates, allows for a systematic way of handling incomplete track-to-track associations across sensors and was presented in preliminary form in [6]. Subsequently, an application to a practical problem was given in [1].

The rest of the paper is organized as follows. The likelihood function of a set of tracks is derived in Section 2. The likelihood ratios for the track-to-track association are presented in Section 3. The assignment with the negative log-likelihood ratios as cost function is discussed in Section 4. An investigation of the assignment accuracy, the sensitivity to the crosscorrelation, and a tracking example are presented in Section 5. Conclusions are in Section 6.

2. THE LIKELIHOOD FUNCTION OF A SET OF TRACKS

Consider the situation where there are S sensors, each with its list of tracks represented by the estimates $\hat{x}_i^{j_i}$ in the same state space, with errors that are zero-mean jointly Gaussian with covariances $P_i^{j_i}$, $i = 1,\ldots,S$, pertaining to a common time (not indicated for simplicity), where subscript i denotes the sensor based on whose data the (local) track has been obtained and superscript $j_i = 1,\ldots,N_i$ denotes the indices of the tracks at sensor i. The error crosscovariances for tracks representing the same target are discussed later.

The likelihood function of the common origin hypothesis $\mathcal{H}_{l_1,\ldots,l_S}$ for the tracks represented by the local estimates $\hat{x}_i^{l_i}$, $i = 1,\ldots,S$, i.e., that they represent the same target is the joint pdf of the "track data" conditioned on the hypothesis

$$\Lambda(\mathcal{H}_{l_1,\ldots,l_S}) = p(\hat{x}_S^{l_S},\ldots,\hat{x}_1^{l_1} \mid \mathcal{H}_{l_1,\ldots,l_S}). \tag{1}$$

Note that in the above we use the fact that the track estimates are sufficient statistics—a consequence of the Gaussian assumption. On the other hand, there is no assumption of independence of the track estimation errors. As it is known, the estimation errors for the same target obtained at independent sensors (with the measurement noises independent across the sensors) are correlated and this is quantified by the crosscovariance matrices (see [2], Sec. 8.4.2). Otherwise, these errors are assumed independent.

The likelihood function (1) can be rewritten by moving the first (or any other) track estimate into the conditioning set, as follows

$$\Lambda(\mathcal{H}_{l_1,\ldots,l_S}) = p(\hat{x}_S^{l_S},\ldots,\hat{x}_2^{l_2} \mid \mathcal{H}_{l_1,\ldots,l_S},\hat{x}_1^{l_1})p(\hat{x}_1^{l_1} \mid \mathcal{H}_{l_1,\ldots,l_S}). \tag{2}$$

Since $\mathcal{H}_{l_1,\ldots,l_S}$ does not contribute any information to the marginal pdf of a single track, it can be dropped from the last term above. Furthermore, the marginal pdf of a track estimate can be taken as diffuse (uniformly distributed in a region of the state space $\mathcal{V}$, whose volume is V, assumed large enough to qualify for a diffuse prior), i.e.,

$$p(\hat{x}_1^{l_1} \mid \mathcal{H}_{l_1,\ldots,l_S}) = p(\hat{x}_1^{l_1}) = \frac{1}{V} \tag{3}$$

because, in the absence of any information (which is our assumption), a track estimate can be anywhere in the state space. This is in accordance to Bayes' postulate [8, 10]. The diffuse prior has to have a support only "sufficiently larger" than the estimates' pdf. Furthermore, this diffuse prior assumption is only for the marginal (unconditional) pdf of a track estimate. The conditional pdf of any track estimate given another estimate with the same origin is not diffuse anymore and is determined by the statistical properties of their estimation errors which are not assumed independent—their correlation can be due to the common process noise as well as to a common prior.

With this, (2) becomes

$$\Lambda(\mathcal{H}_{l_1,\ldots,l_S}) = \frac{1}{V}p(\hat{x}_S^{l_S},\ldots,\hat{x}_2^{l_2} \mid \mathcal{H}_{l_1,\ldots,l_S},\hat{x}_1^{l_1}). \tag{4}$$

Note that V^{-1}, while having a physical dimension (that makes (4) have the same dimension as (1)), is really a constant whose exact value only scales the final result.

Consider first the case of common origin of two tracks, l_i and l_j from sensors i and j, respectively. Now, under the Gaussian assumption, if $\hat{x}_i^{l_i}$ originated from the same target as $\hat{x}_j^{l_j}$, then, with the diffuse prior assumption, one has (see Appendix; this result was presented in [2], Sec. 8.3.3, but without proof)

$$E[\hat{x}_i^{l_i} \mid \mathcal{H}_{l_i,l_j},\hat{x}_j^{l_j}] = \hat{x}_j^{l_j} \tag{5}$$

and

$$\begin{aligned} &E[(\hat{x}_i^{l_i} - \hat{x}_j^{l_j})(\hat{x}_j^{l_j} - \hat{x}_j^{l_j})' \mid \mathcal{H}_{l_i,l_j},\hat{x}_j^{l_j}] \\ &\quad = E[(\hat{x}_i^{l_i} - x^l - (\hat{x}_j^{l_j} - x^l))(\hat{x}_i^{l_i} - x^l - (\hat{x}_j^{l_j} - x^l))' \mid \mathcal{H}_{l_i,l_j}] \\ &\quad = P_i^{l_i} + P_j^{l_j} - P_{i,j}^{l_i,l_j} - (P_{i,j}^{l_i,l_j})' \end{aligned} \tag{6}$$

where x^l is the common true state of these tracks, which is irrelevant. The crosscovariance $P_{i,j}^{l_i,l_j}$ is given by a Lyapunov type recursion (see [2], Sec. 8.4).[1]

The general likelihood function (4) for common origin of the tracks $l_1,\ldots,l_S$ is obtained as follows. The pdf from (4) can be written as

$$p(\hat{x}_S^{l_S},\ldots,\hat{x}_2^{l_2} \mid \mathcal{H}_{l_1,\ldots,l_S},\hat{x}_1^{l_1}) = \mathcal{N}\left(\begin{bmatrix}\hat{x}_2^{l_2}\\ \vdots \\ \hat{x}_S^{l_S}\end{bmatrix};\begin{bmatrix}\hat{x}_1^{l_1}\\ \vdots \\ \hat{x}_1^{l_1}\end{bmatrix},\begin{bmatrix}E[(\hat{x}_2^{l_2}-\hat{x}_1^{l_1})(\hat{x}_2^{l_2}-\hat{x}_1^{l_1})' \mid \mathcal{H}_{l_1,\ldots,l_S}] & \cdots & E[(\hat{x}_2^{l_2}-\hat{x}_1^{l_1})(\hat{x}_S^{l_S}-\hat{x}_1^{l_1})' \mid \mathcal{H}_{l_1,\ldots,l_S}]\\ \cdots & \cdots & \cdots \\ E[(\hat{x}_S^{l_S}-\hat{x}_1^{l_1})(\hat{x}_2^{l_2}-\hat{x}_1^{l_1})' \mid \mathcal{H}_{l_1,\ldots,l_S}] & \cdots & E[(\hat{x}_S^{l_S}-\hat{x}_1^{l_1})(\hat{x}_S^{l_S}-\hat{x}_1^{l_1})' \mid \mathcal{H}_{l_1,\ldots,l_S}]\end{bmatrix}\right). \tag{10}$$

Thus for tracks l_i and l_j one has

$$\begin{aligned}p(\hat{x}_i^{l_i} \mid \mathcal{H}_{l_i,l_j},\hat{x}_j^{l_j}) &= \mathcal{N}[\hat{x}_i^{l_i};\hat{x}_j^{l_j},P_i^{l_i}+P_j^{l_j}-P_{i,j}^{l_i,l_j}-(P_{i,j}^{l_i,l_j})']\\ &= \mathcal{N}[\hat{x}_i^{l_i}-\hat{x}_j^{l_j};0,P_i^{l_i}+P_j^{l_j}-P_{i,j}^{l_i,l_j}-(P_{i,j}^{l_i,l_j})']\end{aligned} \tag{7}$$

where $\mathcal{N}[x;\bar{x},P]$ denotes the Gaussian pdf with argument x, mean $\bar{x}$ and covariance P. Then the joint likelihood function of common origin for the tracks l_i and l_j is

$$\begin{aligned}\Lambda(\mathcal{H}_{l_i,l_j}) &= \frac{1}{V}p(\hat{x}_i^{l_i} \mid \mathcal{H}_{l_i,l_j},\hat{x}_j^{l_j})\\ &= \frac{1}{V}\mathcal{N}[\hat{x}_i^{l_i}-\hat{x}_j^{l_j};0,P_i^{l_i}+P_j^{l_j}-P_{i,j}^{l_i,l_j}-(P_{i,j}^{l_i,l_j})'].\end{aligned} \tag{8}$$

Note that the test statistic (normalized distance squared)

$$D(\hat{x}_i^{l_i},\hat{x}_j^{l_j}) = (\hat{x}_i^{l_i}-\hat{x}_j^{l_j})'[P_i^{l_i}+P_j^{l_j}-P_{i,j}^{l_i,l_j}-(P_{i,j}^{l_i,l_j})']^{-1}(\hat{x}_i^{l_i}-\hat{x}_j^{l_j}) \tag{9}$$

has been known in the literature for some time (e.g., [2], Sec. 8.4.3) for the association of pairs of tracks.[2] While originally this distance was introduced heuristically, it can be seen to follow directly from (8) as a likelihood test. The first rigorous derivation of (9) was given in [17] in the context of sensor bias estimation. The derivation given above is, however, much simpler and, more importantly, it generalizes to S tracks.

Then, similarly to (7), the mean is shifted into the argument and this yields the likelihood function

$$\Lambda(\mathcal{H}_{l_1,\ldots,l_S}) = \frac{1}{V}\mathcal{N}[\hat{\mathbf{x}}_{1,S};0,\mathbf{P}_{1,S}] \tag{11}$$

where

$$\hat{\mathbf{x}}_{1,S} \triangleq \begin{bmatrix}\hat{x}_2^{l_2}-\hat{x}_1^{l_1}\\ \vdots \\ \hat{x}_S^{l_S}-\hat{x}_1^{l_1}\end{bmatrix} \tag{12}$$

is a stacked $(S-1)n_x$ vector (with n_x the dimension of x), whose covariance, defined within (10) has the diagonal blocks

$$\begin{aligned}(\mathbf{P}_{1,S})_{i-1,i-1} &= E[(\hat{x}_i^{l_i}-\hat{x}_1^{l_1})(\hat{x}_i^{l_i}-\hat{x}_1^{l_1})' \mid \mathcal{H}_{l_1,\ldots,l_S}]\\ &= P_1^{l_1}+P_i^{l_i}-P_{1,i}^{l_1,l_i}-(P_{1,i}^{l_1,l_i})',\\ &\qquad i=2,\ldots,S\end{aligned} \tag{13}$$

and the offdiagonal blocks

$$\begin{aligned}(\mathbf{P}_{1,S})_{i-1,j-1} &= E[(\hat{x}_i^{l_i}-\hat{x}_1^{l_1})(\hat{x}_j^{l_j}-\hat{x}_1^{l_1})' \mid \mathcal{H}_{l_1,\ldots,l_S}]\\ &= P_1^{l_1}-P_{1,j}^{l_1,l_j}-(P_{1,i}^{l_1,l_i})'+P_{i,j}^{l_i,l_j},\\ &\qquad i,j=2,\ldots,S.\end{aligned} \tag{14}$$

Note that with the (invertible) transformation

$$\hat{\mathbf{y}}_{1,S} = \begin{bmatrix}1 & -1 & 0 & \cdots\\ 0 & 1 & -1 & 0\\ \cdots & \cdots & \cdots & \cdots\\ \cdots & 0 & 1 & -1\\ \cdots & 0 & 0 & 1\end{bmatrix}\hat{\mathbf{x}}_{1,S} = \begin{bmatrix}\hat{x}_2^{l_2}-\hat{x}_3^{l_3}\\ \hat{x}_3^{l_3}-\hat{x}_4^{l_4}\\ \vdots \\ \hat{x}_{S-1}^{l_{S-1}}-\hat{x}_S^{l_S}\\ \hat{x}_S^{l_S}-\hat{x}_1^{l_1}\end{bmatrix} \tag{15}$$

one can see that (11) is really symmetric in the sense that it has an equivalent symmetric form even if it appears not to be symmetric at first sight. This is due to the fact that the determinant of the above transformation is unity.

[1]Previous communication is difficult to account for in the correlation but not impossible—this would require restarting (after every communication) the iteration of the Lyapunov equation (8.4.2-3) in [2] that yields the crosscovariance.

[2]The importance of using the crosscovariances is twofold: ignoring the crosscorrelations (which are positive, as discussed in Section 5) the distance (9) is smaller than it should be and the covariance of the fused estimate is optimistic (see [2], Sec. 8.4.5).

REMARKS Note that the expression of the likelihood function (11) follows from the way in which (4) is written, namely as the joint pdf of the local track estimates from sensors $S,\ldots,2$ (written for convenience with the indices decreasing) conditioned on the track estimate from sensor 1. Equation (4) can be rewritten in the chain rule form as

$$\Lambda(\mathcal{H}_{l_1,\ldots,l_S}) = \frac{1}{V}\prod_{i=2}^{S} p(\hat{x}_i^{l_i} \mid \hat{x}_{i-1}^{l_{i-1}},\ldots,\hat{x}_2^{l_2},\hat{x}_1^{l_1})$$

$$= \frac{1}{V}\prod_{i=2}^{S} p(\hat{x}_i^{l_i} \mid \hat{x}^{F^{i-1}}) \tag{16}$$

where $\hat{x}^{F^{i-1}}$ is the fused state estimate from the first $i-1$ local tracks.

It was this last form that was derived in [14] under the assumption that the local track errors are uncorrelated. While (16) holds also for correlated tracks since no uncorrelatedness assumption was needed in its derivation above, its evaluation is relatively simple only under the assumption that the local track errors are uncorrelated. Otherwise, for the realistic situation of correlated track errors it becomes quite complicated. Consequently, expression (11) is believed to be the practical one when the crosscovariances are taken into consideration.

Note that the local track estimate from sensor 1 is chosen in the conditioning of (2) only for notational simplicity. One can use any local estimate as the reference track to obtain (11) with similar derivation.

3. THE LIKELIHOOD RATIOS FOR GENERAL TRACK-TO-TRACK ASSOCIATION

The likelihood ratio of the common origin hypothesis $\mathcal{H}_{l_1,\ldots,l_S}$ for the tracks represented by the local estimates $\hat{x}_i^{l_i}$, $i = 1,\ldots,S$, i.e., that all these tracks represent the same target is obtained next. The numerator is given by (11) while the denominator, which is the likelihood of all being of different origin (hypothesis $\bar{\mathcal{H}}_{l_1,\ldots,l_M}$), is obtained in a similar manner to (2) as follows

$$\Lambda(\bar{\mathcal{H}}_{l_1,\ldots,l_S}) = p(\hat{x}_S^{l_S},\ldots,\hat{x}_2^{l_2} \mid \bar{\mathcal{H}}_{l_1,\ldots,l_S},\hat{x}_1^{l_1})p(\hat{x}_1^{l_1} \mid \bar{\mathcal{H}}_{l_1,\ldots,l_S})$$

$$= \prod_{s=2}^{S} p(\hat{x}_s^{l_s} \mid \bar{\mathcal{H}}_{l_1,\ldots,l_S},\hat{x}_1^{l_1})p(\hat{x}_1^{l_1} \mid \bar{\mathcal{H}}_{l_1,\ldots,l_S}). \tag{17}$$

Analogously to (3),

$$p(\hat{x}_1^{l_1} \mid \bar{\mathcal{H}}_{l_1,\ldots,l_S}) = p(\hat{x}_1^{l_1}) = \frac{1}{V}. \tag{18}$$

As shown in [7], [10], the role of the pdf of a false/extraneous measurement in the likelihood ratio is played by the spatial density of these measurements under the assumption that they are Poisson distributed. This was obtained from the rigorous Bayesian derivation of the Multiple Hypothesis Tracker. Consequently, assuming the extraneous tracks in the present problem to be Poisson distributed in the state space with spatial density[3] μ_{ex}, one has

$$p(\hat{x}_s^{l_s} \mid \bar{\mathcal{H}}_{l_1,\ldots,l_S},\hat{x}_1^{l_1}) = \mu_{\text{ex}}. \tag{19}$$

Using (18) and (19) in (17) yields

$$\Lambda(\bar{\mathcal{H}}_{l_1,\ldots,l_S}) = \frac{\mu_{\text{ex}}^{S-1}}{V}. \tag{20}$$

Finally, combining the above with (11) yields the likelihood ratio

$$\mathcal{L}(\mathcal{H}_{l_1,\ldots,l_S} : \bar{\mathcal{H}}_{l_1,\ldots,l_S}) = \frac{\Lambda(\mathcal{H}_{l_1,\ldots,l_S})}{\Lambda(\bar{\mathcal{H}}_{l_1,\ldots,l_S})} = \frac{\frac{1}{V}\mathcal{N}[\hat{\mathbf{x}}_{1,S};0,\mathbf{P}_{1,S}]}{\frac{1}{V}\mu_{\text{ex}}^{S-1}}$$

$$= \frac{\mathcal{N}[\hat{\mathbf{x}}_{1,S};0,\mathbf{P}_{1,S}]}{\mu_{\text{ex}}^{S-1}} \tag{21}$$

which is, clearly, a dimensionless quantity.

Next consider the likelihood ratio of an incomplete assignment consisting of tracks from the lists corresponding to the subset of sensors with indices $\mathcal{S}_i = \{s_1,s_2,\ldots,s_M\}$, where $1 \le s_1 < s_2 < \cdots < s_M \le S$. The entire set of list (sensor) indices is denoted as $\mathcal{S}$.

Assume that the probability of a target having a ("detected") track in the list of sensor s is P_{D_s} and that these track detection events are independent across sensors.[4]

Then the likelihood ratio of this assignment is [7]

$$\mathcal{L}(\mathcal{H}_{l_{s_1},\ldots,l_{s_M}} : \bar{\mathcal{H}}_{l_{s_1},\ldots,l_{s_M}})$$

$$= V^{-1}\mathcal{N}[\hat{\mathbf{x}}_{\mathcal{S}_i};0,\mathbf{P}_{\mathcal{S}_i}]\left[\prod_{s\in\mathcal{S}_i} P_{D_s}\right]\mu_{\text{ex}}^{-S+M}$$

$$\times\left[\prod_{s\in\bar{\mathcal{S}}_i}(1-P_{D_s})\right][V^{-1}\mu_{\text{ex}}^{-S+1}]^{-1}$$

$$= \mu_{\text{ex}}^{M-1}\mathcal{N}[\hat{\mathbf{x}}_{\mathcal{S}_i};0,\mathbf{P}_{\mathcal{S}_i}]\left[\prod_{s\in\mathcal{S}_i} P_{D_s}\right]\left[\prod_{s\in\bar{\mathcal{S}}_i}(1-P_{D_s})\right]. \tag{22}$$

The above follows by including in the numerator the probabilities of the events (assumed independent) that the tracks belonging to the hypothesized target have been detected by the sensors in $\mathcal{S}_i$ but not by the

[3]Since the true targets are typically not homogeneously distributed in the space, this should be taken as the local density of the extraneous (true and false) tracks.

[4]This is clearly only a convenient mathematical assumption—in practice the situation can be much more complex: these probabilities depend on the target locations, sensor modes, their fields of view, obscuration conditions, etc.

sensors in $\bar{\mathcal{S}}_i$. For the tracks corresponding to the sensors in $\bar{\mathcal{S}}_i$, their pdfs are the "extraneous" ones, μ_{ex}. In the denominator we have the probability densities of the tracks assuming they are not of common origin, modeled as having pdfs μ_{ex}. The pdfs of the tracks corresponding to the sensors in $\bar{\mathcal{S}}_i$ cancel between the numerator and denominator.

The first argument of the Gaussian density in (22) is, similarly to (12), given by

$$\hat{\mathbf{x}}_{\mathcal{S}_i} \triangleq \begin{bmatrix} \hat{x}_{s_2}^{l_{s_2}} - \hat{x}_{s_1}^{l_{s_1}} \\ \vdots \\ \hat{x}_{s_M}^{l_{s_M}} - \hat{x}_{s_1}^{l_{s_1}} \end{bmatrix} \tag{23}$$

and $\mathbf{P}_{\mathcal{S}_i}$ is its covariance matrix with blocks given by expressions similar to (13)–(14).

4. THE USE OF THE LIKELIHOOD RATIOS IN ASSIGNMENT

We first consider the assignment formulation for track-to-track association from two sensors. Assume sensor 1 has a list of N_1 tracks and sensor 2 has a list of N_2 tracks. Define the binary assignment variable χ_{ij} as

$$\chi_{ij} = \begin{cases} 1 & \text{track } i \text{ from sensor 1 and track } j \\ & \text{from sensor 2 are from the same target,} \\ 0 & \text{otherwise.} \end{cases} \tag{24}$$

Denote by $\mathcal{L}_{ij}$ the likelihood ratio of the two tracks being from the same target vs. from two different targets which is the two sensor case of (22). If we assume that the track association events among different track pairs are independent, then the 2-D assignment formulation finds the most likely (joint) track-to-track association hypothesis by solving the following constrained optimization[5]

$$\min_{\chi_{ij}} \sum_{i=0}^{N_1} \sum_{j=0}^{N_2} c_{ij} \chi_{ij} \tag{25}$$

subject to

$$\sum_{i=0}^{N_1} \chi_{ij} = 1, \qquad j = 1,\ldots,N_2 \tag{26}$$

$$\sum_{j=0}^{N_2} \chi_{ij} = 1, \qquad i = 1,\ldots,N_1 \tag{27}$$

$$\chi_{ij} \in \{0,1\}, \qquad i = 0,1,\ldots,N_1, \quad j = 0,1,\ldots,N_2 \tag{28}$$

where

$$c_{ij} = -\ln \mathcal{L}_{ij}. \tag{29}$$

This can be solved using the Auction or JVC algorithm [19]. As shown in [12] this can also be solved optimally using linear programming by relaxing the integer constraint.

The extension to multidimensional assignment (S-D) is as follows. Assume there are S sources ($S \geq 3$) where source S_i has a list of N_i tracks. Define the binary assignment variable $\chi_{i_1 i_2 \ldots i_S}$ as

$$\chi_{i_1 i_2 \ldots i_S} = \begin{cases} 1 & \text{tracks } i_1, i_2, \ldots, i_S \text{ are from the same target,} \\ 0 & \text{otherwise.} \end{cases} \tag{30}$$

We allow a subset of indices $\{i_1, i_2, \ldots, i_s\}$ to be zero in the assignment variable meaning that no track will be from the target in the corresponding list of the sources. Denote by $\mathcal{L}_{i_1 i_2 \ldots i_S}$ the likelihood ratio of the track association hypothesis vs. all tracks being from different targets which is given by (22). The S-D assignment formulation finds the most likely hypothesis by solving the following constrained optimization

$$\min_{\chi_{i_1 i_2 \ldots i_S}} \sum_{i_1=0}^{N_1} \sum_{i_2=0}^{N_2} \cdots \sum_{i_S=0}^{N_S} c_{i_1 i_2 \ldots i_S} \chi_{i_1 i_2 \ldots i_S} \tag{31}$$

subject to

$$\begin{aligned} \sum_{i_2=0}^{N_2} \cdots \sum_{i_S=0}^{N_S} \chi_{j i_2 \ldots i_S} &= 1, \qquad j = 1,\ldots,N_1 \\ \sum_{i_1=0}^{N_1} \sum_{i_3=0}^{N_3} \cdots \sum_{i_S=0}^{N_S} \chi_{i_1 j i_3 \ldots i_S} &= 1, \qquad j = 1,\ldots,N_2 \\ &\cdots \\ \sum_{i_1=0}^{N_1} \cdots \sum_{i_{S-1}=0}^{N_{S-1}} \chi_{i_1 i_2 \ldots i_{S-1} j} &= 1, \qquad j = 1,\ldots,N_S \end{aligned} \tag{32}$$

and

$$\begin{gathered} \chi_{i_1 i_2 \ldots i_S} \in \{0,1\}, \\ i_1 = 0,1,\ldots,N_1, \quad i_2 = 0,1,\ldots,N_2 \quad ,\ldots, \quad i_S = 0,1,\ldots,N_S. \end{gathered} \tag{33}$$

In (31) the assignment cost is

$$c_{i_1 i_2 \ldots i_S} = -\ln \mathcal{L}_{i_1 i_2 \ldots i_S} \tag{34}$$

where the likelihood ratio $\mathcal{L}_{i_1 i_2 \ldots i_S}$ (written here with a simpler index-only notation) can be computed using (22). The above constrained integer programming is, in general, NP hard. However, efficient algorithms exist to find a suboptimal solution via Lagrangian relaxation (see, e.g., [19]).

[5] Each list of tracks from a sensor is augmented by a "dummy element" with index 0, which stands for "no track," to allow for incomplete associations, while keeping the assignment problem complete.

5. SIMULATION RESULTS

5.1 Evaluation of the Association Accuracy and Sensitivity

We want to study the track association accuracy for a different number of local sensors with various crosscorrelation coefficients. To make it simple, we assume that the local estimates are scalars with unity variances. The crosscorrelation coefficients between two local estimates is denoted by ρ. We choose various values of ρ, namely, 0, 0.1, 0.3, 0.5, when the local tracks correspond to the same target.

The null hypothesis H_0 is that all the local estimates correspond to the same target with its location uniformly distributed within the surveillance region of length $V = 10$

$$H_0 = \{\text{“same target”}\}. \tag{35}$$

The hypothesis H_1 is that all local estimates correspond to different targets with their locations uniformly distributed within the surveillance region

$$H_1 = \{\text{“different targets”}\}. \tag{36}$$

In this case, the separation of two targets is random and it depends on the volume of the surveillance region and no further prior knowledge is assumed.

Note that with the relatively small region V the targets, even if they are different, can be close enough to appear as they were the same, i.e., it is difficult to discriminate between the two hypotheses because they are not easily distinguishable. Consequently, even the most powerful test will not be very powerful is this situation.

The test based on (22) is used to compute the receiver operating characteristic (ROC) curves for the cases of N local tracks from the same target, i.e., the curves of the power of the test

$$P_D = P\{\text{“}H_0\text{”} \mid H_0\} \tag{37}$$

where “H_0” denotes “accept H_0,” vs. the false alarm probability

$$P_{FA} = P\{\text{“}H_0\text{”} \mid H_1\}. \tag{38}$$

Fig. 1 shows the ROC curves for the track association test with 2, 3, and 4 local track estimates and various crosscorrelation coefficients. One thousand random realizations are used for each hypothesis with fixed ρ and N to compute these curves. We can see that the test power increases as N increases for fixed V since the H_0 hypothesis becomes more distinguishable when more targets are uniformly distributed within the surveillance region. The crosscorrelation between the local track estimates is beneficial in terms of the test power under a given false alarm rate for all cases. As ρ increases, the alternative hypothesis (“different targets”) becomes more distinguishable from the null hypothesis (“same target”) because common origin tracks will then be closer to each other (in terms

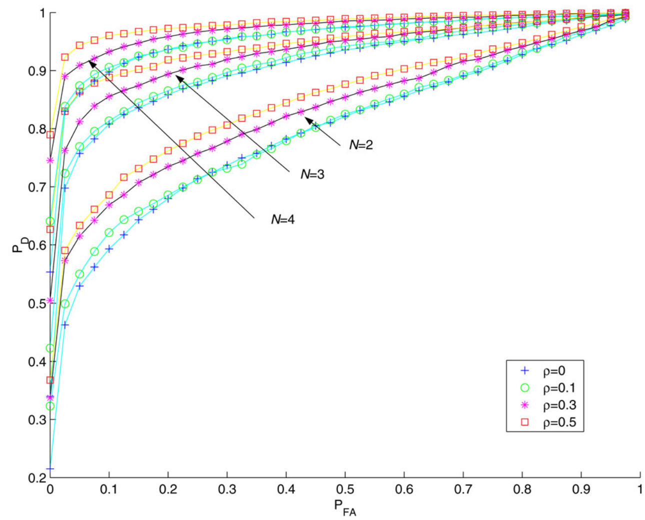

Fig. 1. ROC curves for the track association test with a different number of local estimates and various crosscorrelation coefficients.

of their normalized distance—see (9), which improves the decision accuracy. However, once H_0 is declared, the variance of the fused track estimate is larger than when they are uncorrelated [11].

Consider a case where one uses the test assuming $\rho = 0$. The threshold is determined for a certain maximum allowed miss probability of H_0, that is, $1 - P_D$. If the true crosscorrelation coefficient is, e.g., $\rho = 0.5$, the actual P_D will be higher than the one calculated under $\rho = 0$. At the same time, the actual P_{FA} will also be higher.

For two tracks (each with unity variance, for simplicity) assuming $\rho = 0$, the (chi-square) test statistic used is

$$D_0 = (\hat{x}_1 - \hat{x}_2)^2/2 \tag{39}$$

and the “design” probability of falsely rejecting the null hypothesis is

$$P\{D_0 > \tau_0 \mid H_0\} = 1 - P_D^0 \tag{40}$$

based on the chi-square distribution with one degree of freedom

$$D_0 \sim \chi_1^2. \tag{41}$$

However, since $\rho = 0.5$, (41) does not hold, Instead, under H_0,

$$D = (\hat{x}_1 - \hat{x}_2)^2/[2(1-\rho)] \sim \chi_1^2. \tag{42}$$

Thus the test statistic used, D_0, is

$$D_0 = D/2 \tag{43}$$

i.e., half of what it should have been. Consequently, the statistic D_0 will be more inclined to accept the “same target” hypothesis than the correct statistic D, i.e., P_{FA}, as well as P_D, will increase. Because the test statistic used is a scaled version of the correct one, the test assuming $\rho = 0$ uses effectively a threshold that is double of what it would have been with $\rho = 0.5$. Thus the ROC for the test assuming $\rho = 0$ is the one with the true $\rho = 0.5$ but the operating point on it is different than the "design operating point."

This can be illustrated on Fig. 1. Assume $N = 3$ and the design operating point (on the $\rho = 0$ ROC curve) is $P_D = 0.83$, $P_{FA} = 0.025$. The actual operating point for this test is on the $\rho = 0.5$ ROC curve at $P_D = 0.86$, $P_{FA} = 0.05$. Note the sensitivity of the actual FA rate to ignoring the crosscorrelation: it is twice the design value.

5.2 A Multisensor Tracking Example

We consider a target tracking scenario where three sensors are located at $(-50, 0)$ km, $(0, 187)$ km, and $(50, 0)$ km, respectively. All three sensors measure the target range and bearing with the same standard deviations of the measurement error given by $\sigma_r = 50$ m and $\sigma_b = 2$ mrad. The sampling interval of sensors 1 and 2 is $T_1 = T_2 = 2$ s while the sampling interval of sensor 3 is $T_3 = 5$ s.

The two targets in the scenario considered are initially at $(0, 86.6)$ km and $(0.4, 86.6)$ km, respectively. Both targets move in parallel with a speed of 300 m/s. The motion of the two targets is characterized as follows. Both targets initially move south-east on a course of approximately 135°. Then at $t = 15$ s both targets make a course change with a constant turn rate of 4°/s (acceleration of about 2.1 g over a duration T_{man} of about 11 s) and head east. Both targets make a second course change at $t = 35$ s with a constant turn rate of 4°/s and head north-east. The trajectories of the two targets are shown in Fig. 2 where the true target positions are indicated at the time instances at which a measurement is made by one of the three sensors. The total time for the two targets to complete the designated trajectories is 60 s. Note that the target ranges are around 100 km at the beginning for all sensors, where the standard deviation of the crossrange measurement is around 200 m. Thus the tracker has measurement origin uncertainty when updating the target state estimates. The true target motion has a random acceleration from a white process noise with power spectral density (PSD) $q = 1$ m^2/s^3 in each realization. We assume that the two targets have unity detection probability by each sensor and there are no false measurements, i.e., each sensor has both tracks and no false tracks—in this case there are no incomplete associations to consider (see [1] for a problem with incomplete associations). The results presented are based on 100 Monte Carlo runs.

Two tracking configurations for performance comparison are implemented as follows.

i) A centralized estimator which uses an IMM with two models and sequentially updates the target state with measurements from sensors 1–3. This IMM estimator has a discretized continuous white noise acceleration (DCWNA) model (see [4], Sec. 6.2.2) with low

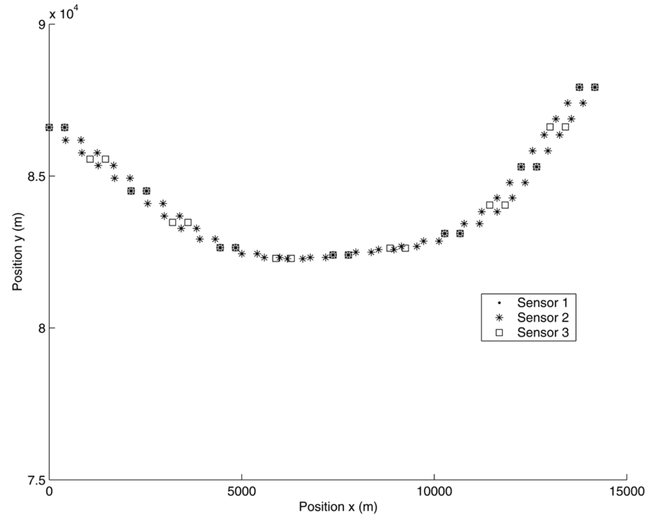

Fig. 2. Target trajectories with true positions at the times when measurements are made by the sensors.

process noise power q_l to capture the uniform target motion and a DCWNA model with high process noise PSD q_h to capture the two turns. We use $q_l = 1$ m^2/s^3 and $q_h = 8000$ m^2/s^3 which, for $T_{\text{man}} = 11$ s, corresponds to a target average acceleration of $\sqrt{q_h/T_{\text{man}}} \approx 2.6$ g. The process noise is the same in east and north of the Cartesian coordinates and uncorrelated between these coordinates. The transition between the modes is modelled according to a continuous time Markov chain with the expected sojourn times ([4], Sec. 11.7.3) in these modes given by $1/\lambda_1$ and $1/\lambda_2$, respectively. These correspond to exponential sojourn time distributions with parameters λ_1 and λ_2, respectively. The transition probability matrix between the two models (generalized version of (11.6.7-1) in [4]) from any time t_1 to time t_2 is [18]

$$\Pi(t_2, t_1) = \frac{1}{\lambda_1 + \lambda_2} \begin{bmatrix} \lambda_2 + \lambda_1 e^{-(\lambda_1+\lambda_2)T} & \lambda_1 - \lambda_1 e^{-(\lambda_1+\lambda_2)T} \\ \lambda_2 - \lambda_2 e^{-(\lambda_1+\lambda_2)T} & \lambda_1 + \lambda_2 e^{-(\lambda_1+\lambda_2)T} \end{bmatrix} \tag{44}$$

where $T = |t_2 - t_1|$. For the scenario used in simulation, we chose $\lambda_1 = \frac{1}{20}$ s^{-1} and $\lambda_2 = \frac{1}{10}$ s^{-1}. For the centralized IMM estimator, 2-D assignment is used to solve the measurement-to-track association problem and the most likely hypothesis is chosen for the filter update.

ii) In the decentralized tracking configuration each sensor uses an IMM estimator and the fusion center fuses the local estimates every $T_F = 10$ s using all local state estimates and the corresponding covariances with approximate crosscovariances. For each local IMM estimator, 2-D assignment is used to solve the measurement-to-track association problem and the most likely hypothesis is chosen for the filter update. The track-to-track association is based on the most likely hypothesis obtained by solving the 3-D assignment. If the local tracks are declared as from the same target, then the track-to-track fusion is car-

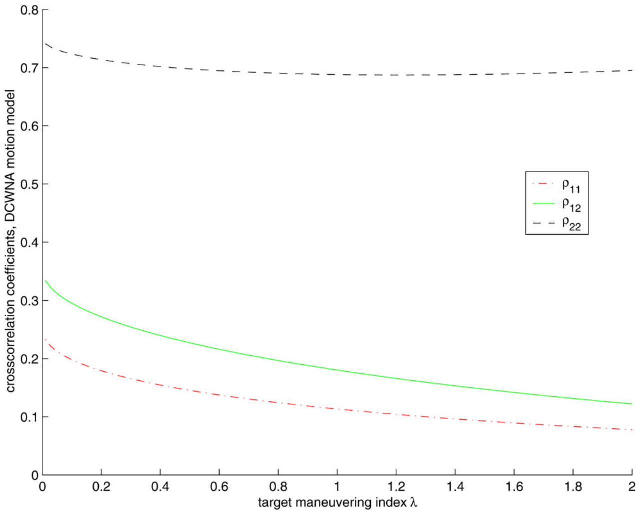

Fig. 3. Crosscorrelation coefficients vs. target maneuvering index for DCWNA model. ρ_{11}: position-position, ρ_{12}: position-velocity, ρ_{22}: velocity-velocity.

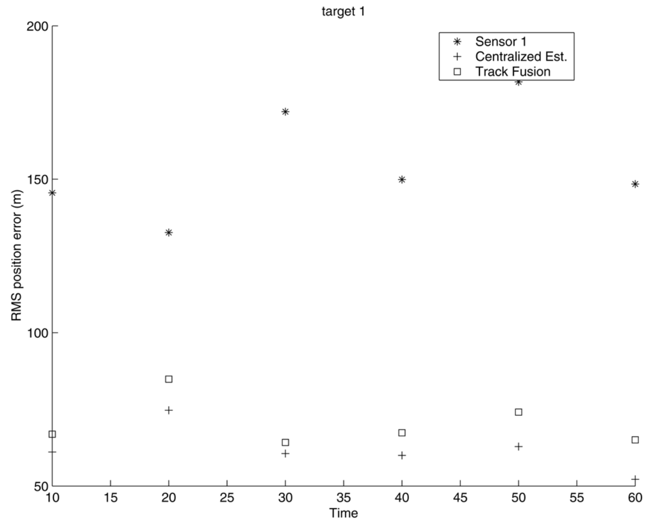

Fig. 4. Comparison of the RMS position errors for centralized IMM estimator (configuration (i)), track fusion from three IMM estimators (configuration (ii)) for target 1; local IMM estimator from sensor 1 also shown.

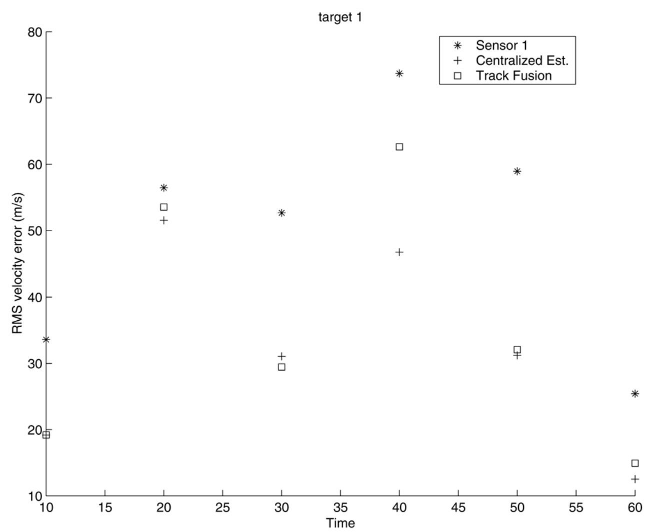

Fig. 5. Comparison of the RMS velocity errors for centralized IMM estimator (configuration (i)), track fusion from three IMM estimators (configuration (ii)) for target 1; local IMM estimator from sensor 1 also shown.

ried out with an approximate crosscovariance matrix, as in [11].

The combined estimates and their covariances generated by the IMM were used in the association and the corresponding state errors were approximated as Gaussian. The crosscovariance used at the fusion center is calculated using the fixed crosscorrelation coefficients detailed below. Assuming equal variances of the measurement error for both sensors, we can solve the Lyapunov equation for the steady state discretized continuous-time white noise acceleration (DCWNA) model ([2], Sec. 6.2.2). The resulting crosscorrelation coefficients between the estimation errors from the two local trackers are shown in Fig. 3 for the target maneuvering index[6] within (0.05, 2). In the simulation, we used the following fixed values for the crosscorrelation coefficients: $\rho_{11} = 0.15$ (position-position), $\rho_{12} = 0.25$ (position-velocity) and $\rho_{22} = 0.7$ (velocity-velocity) to obtain an approximate crosscovariance matrix between the local track pairs (see [11]) which was then used in the optimal track-to-track fusion algorithm.

Figs. 4 and 7 show the RMS position errors at the fusion center for the above two tracking configurations as well as that by sensor 1 alone for target 1 and target 2. Figs. 5 and 8 show the corresponding RMS velocity errors for target 1 and target 2. We can see that the track fusion of three local IMM estimators (configuration (ii)) has the RMS errors close to that of the centralized estimator (configuration (i)). Thus the proposed assignment solution to the track-to-track association is very effective when the consistency of the local tracks is good. Figs. 6 and 9 show the normalized estimation error squared (NEES, see [4], Sec. 5.4.2) at the fusion center for the above two tracking configurations as well as that by sensor 1 alone. We can see that the distributed track fusion yields larger NEES than the centralized estimator during the target turns. Thus caution has to be exercised when fusing the local estimates that are not credible on their own NEES statistics.[7]

[6]The target maneuvering index for a DCWNA model is given by $\sqrt{qT^3/\sigma_w}$ where q is the process noise PSD, T the sampling interval and σ_w the measurement noise standard deviation [4], Sec. 6.5.4.

[7]While, for maneuvering targets, the IMM estimator is superior, in terms of its NEES consistency, compared to a fixed model Kalman filter due to its adaptability, this adaptation takes about 2 sampling intervals, during which it can experience short-term inconsistency (see [4], Sec. 11.7).

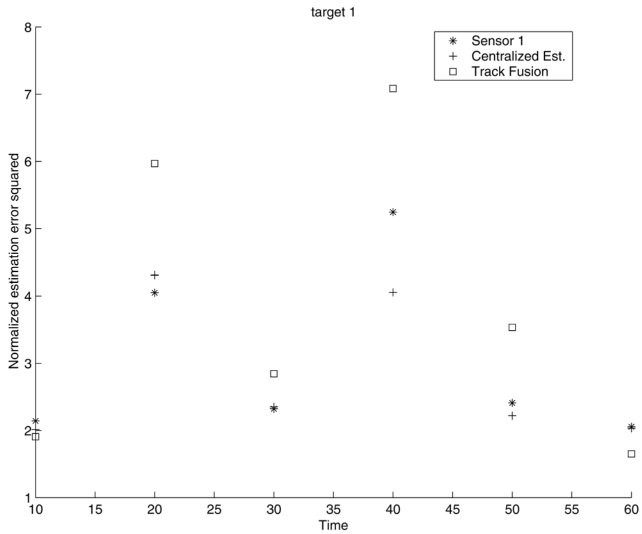

Fig. 6. Comparison of the NEES for centralized IMM estimator (configuration (i)), track fusion from three IMM estimators (configuration (ii)) for target 1; local IMM estimator from sensor 1 also shown.

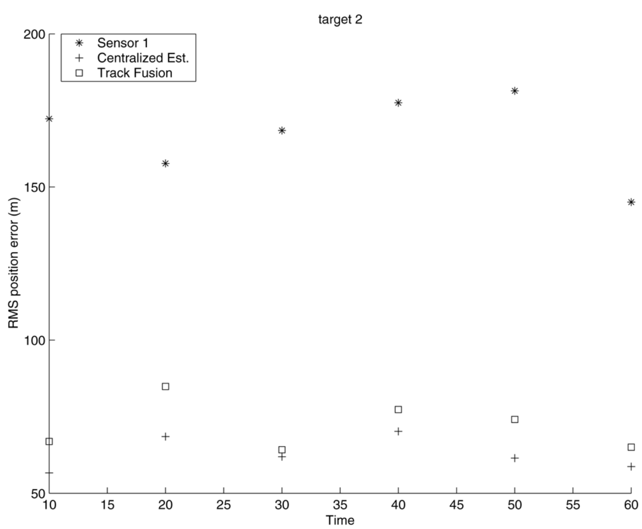

Fig. 7. Comparison of the RMS position errors for centralized IMM estimator (configuration (i)), track fusion from three IMM estimators (configuration (ii)) for target 2; local IMM estimator from sensor 1 also shown.

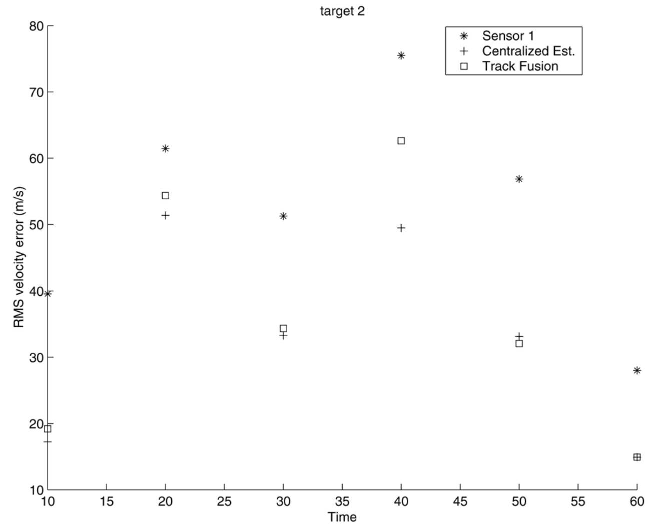

Fig. 8. Comparison of the RMS velocity errors for centralized IMM estimator (configuration (i)), track fusion from three IMM estimators (configuration (ii)) for target 2; local IMM estimator from sensor 1 also shown.

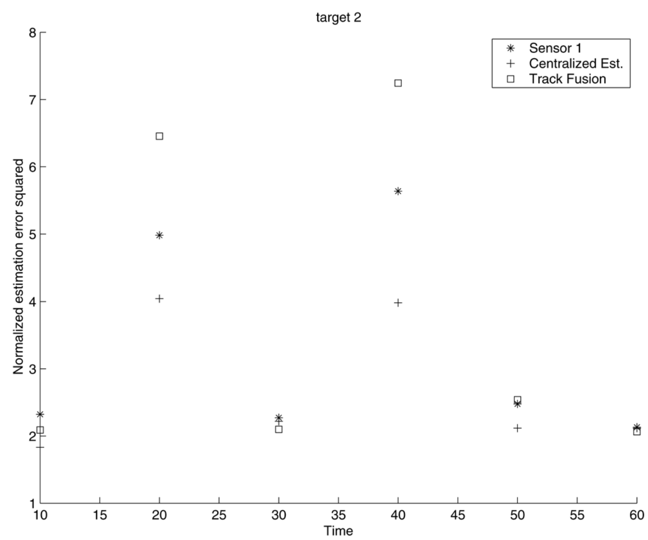

Fig. 9. Comparison of the NEES for centralized IMM estimator (configuration (i)), track fusion from three IMM estimators (configuration (ii)) for target 2; local IMM estimator from sensor 1 also shown.

The ML assignment for track-to-track association from the 3 sensors over the 100 runs yielded in all runs the correct association.

6. SUMMARY AND CONCLUSIONS

In this paper the problem of track-to-track association from an arbitrary number of sources was considered where tracks of the same target obtained from different sensors have dependent estimation errors. The exact likelihood function for the track-to-track association problem from multiple sources was derived. This forms the basis for the likelihood ratio cost function used in a multidimensional assignment algorithm that can solve such a large scale data association problem. Simulation results using a two-target three-sensor tracking scenario show that the estimation errors of the distributed track fusion with the assignment solution to the track association problem are only slightly larger than those of the centralized estimator. These results are in line with those of [5].

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APPENDIX. THE PDF OF A STATE ESTIMATE CONDITIONED ON ANOTHER STATE ESTIMATE

Under the common origin hypothesis $\mathcal{H}_{l_i,l_j}$ one has

$$\hat{x}_j^{l_j} = x - \tilde{x}_j^{l_j} \tag{45}$$

and

$$\hat{x}_i^{l_i} = x - \tilde{x}_i^{l_i} \tag{46}$$

where x is the common true state.

Equations (45)–(46) yield

$$\hat{x}_i^{l_i} = \hat{x}_j^{l_j} + \tilde{x}_j^{l_j} - \tilde{x}_i^{l_i}. \tag{47}$$

If the prior (unconditional) pdf of a state estimate $\hat{x}_j^{l_j}$ is diffuse (noninformative or improper [4]), it follows from (45) that the prior of the true state x is also diffuse because

1) x and $\tilde{x}_j^{l_j}$ are independent,

2) the error $\tilde{x}_j^{l_j}$ has a proper prior pdf, and

3) in order for the convolution of the pdfs of x and $\tilde{x}_j^{l_j}$ to yield a diffuse pdf for $\hat{x}_j^{l_j}$ (as assumed), the (prior) pdf of x has to be also diffuse.

Consequently, $\tilde{x}_j^{l_j}$ is independent of $\hat{x}_j^{l_j}$ since there is no inference one can make on $\tilde{x}_j^{l_j}$ from $\hat{x}_j^{l_j}$ because their relationship contains x, which has a diffuse prior pdf.

Thus

$$E[\tilde{x}_j^{l_j} \mid \hat{x}_j^{l_j}] = 0 \tag{48}$$

and, similarly

$$E[\tilde{x}_i^{l_i} \mid \hat{x}_j^{l_j}] = 0. \tag{49}$$

The conditional expectation of (47) can the be written using (48)–(49) as

$$E[\hat{x}_i^{l_i} \mid \mathcal{H}_{l_i,l_j}, \hat{x}_j^{l_j}] = E[\hat{x}_j^{l_j} + \tilde{x}_j^{l_j} - \tilde{x}_i^{l_i} \mid \mathcal{H}_{l_i,l_j}, \hat{x}_j^{l_j}] = \hat{x}_j^{l_j} \tag{50}$$

which proves (5). Equation (6) follows in a similar manner.

Finally, because all the state errors are assumed Gaussian, the conditional pdf of a state estimate in terms of another state estimate (7) follows.

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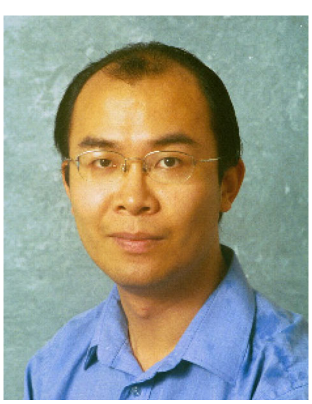

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