IPDAF in Distributed Sensor Networks for tracking an occulted ground-target in clutter

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Abstract - ***An improved version of the Integrated Probabilistic Data Association Filter (IPDAF) and the IJPDAF based on a new concept of probability of target perceivability has been recently introduced for tracking one or several targets by a single sensor. IPDAF and IJPDAF algorithms allow to perform online track initiation, maintenance, confirmation and termination as well using an appropriate target perceivability probability decision logic. This paper deals with the development of a DSN (Distributed Sensor Networks) version of the new IPDAF algorithm. Simulation results of this new DSN/IPDAF algorithm for tracking a single occasionally occulted ground-target in a cluttered urban environment is presented for a simple 2D scenario.***

Keywords: Distributed Estimation, Multisensor Target Tracking, IPDAF, DSN, perceivability.

1 Introduction

A distributed sensor network (DSN) is a set of sensors connected by a communication network to a set of local processing nodes. These nodes process measurements and communicate among themselves in order to track the target. An important problem in distributed tracking is how to decide whether local tracks delivered at the local processing level represent the same target. We assume here that this track-to-track association problem has been solved (see [6] for discussion). In previous works done by K.C. Chang and al. during last decade [9, 7, 8, 10, 11, 21], the DSN sensor target tracking problem has been solved on the basis of classical PDAF and/or JPDAF algorithms (also coupled with Interacting Multiple Model (IMM) approach for maneuvering target tracking). It has already been shown that performances obtained with distributed estimation algorithms are very close to the optimal performance obtained by a centralized estimation algorithm. Moreover it is well known that DSN has many advantages over a centralized system in terms of reliability, extended coverage, better use of information and so forth. These Distributed PDAF/JPDAF algorithms have however been developed with an implicit strong assumption that the targets are *always perceivable* by the sensors. A target is said to be perceivable if it is present in the environment and not hidden/occulted in the field of view of the sensor. Of course in many real situations and like the one described in this paper, this is not always the case. To remove this total perceivability assumption, new versions of the Integrated Probabilistic Data Association Filter (IPDAF) and IJPDAF for a single sensor/tracker have been developed recently in [14, 13] which includes a more rigourous concept of target perceivability [15, 18] into its formalism than privious works of Colegrove [12] and Musicki [22]. Herafter we extent this new IPDAF for DNS in order to extend their application fields to more realistic situations.

2 Problem formulation

We consider an s-node distributed sensor network as in [8] where each node processes the local measurements from its own sensor based on a local IPDAF and sends the local estimates to the fusion processor periodically. The fusion processor then sends back the processed results after each communication time. The dynamic of the target in track is modeled as

$$\mathbf{x}(k+1) = \mathbf{F}(k)\mathbf{x}(k) + \mathbf{v}(k) \qquad (1)$$

where $\mathbf{x}(k)$ is the state vector and $\mathbf{v}(k)$ is the process noise assumed to be zero-mean and Gaussian with a known covariance matrix $\mathbf{Q}(k)$. The target detection probability P_d^i for each sensor i is assumed to be known. The equation measurement for the target relative to sensor i is

$$\mathbf{z}^i(k) = \mathbf{H}^i(k)\mathbf{x}(k) + \mathbf{w}^i(k) \tag{2}$$

where $\mathbf{H}^i(k)$ is a known observation matrix and $\mathbf{w}^i(k)$ is the corresponding measurement noise assumed to be zero-mean, Gaussian with a given covariance $\mathbf{R}^i(k)$. Furthermore noise sequences $\{\mathbf{v}(k)\}$ and $\{\mathbf{w}^i(k)\}$ $(k = 1, 2, \dots)$ are assumed to be mutually independent and independent of initial state vector $\mathbf{x}(0)$.

The classical gating technique [4] with a given probability P_g^i $(i = 1, \dots, s)$ is used for the selection of measurements. For each sensor $i = 1, \dots, s$, the set of the m_k^i validated measurement at time k and the cumulative set of measurements are denoted

$$\mathbf{Z}^i(k) = \{\mathbf{z}^i_{j_i}(k)\}_{j_i=1}^{m_k^i} \quad \text{and} \quad \mathbf{Z}^{i,k} = \{\mathbf{Z}^i(l)\}_{l=1}^{k}$$

The distributed estimation problem we have to solve is the reconstruction of the global conditional pdf $p(\mathbf{x}(k)|\mathbf{Z}^{1,k}, \dots, \mathbf{Z}^{s,k})$ from the local ones $p(\mathbf{x}(k)|\mathbf{Z}^{1,k}), \dots, p(\mathbf{x}(k)|\mathbf{Z}^{s,k})$. Under linear models and Gaussian noise assumptions, this problem reduces to evaluate $\hat{\mathbf{x}}(k|k) = E[\mathbf{x}(k)|\mathbf{Z}^{1,k}, \dots, \mathbf{Z}^{s,k}]$ from local estimates with its covariance $\mathbf{P}(k|k)$.

3 The Local IPDAF

At a given node associated with a sensor s, the local tracking is assumed to be done with the new IPDAF. This tracking filter is an extension of the classical PDAF which integrates the concept of target perceivability.

At any time k, the target state of perceivability with respect to a given sensor s and its complement is represented by the exhaustive and exclusive events

$$\begin{aligned} O_k^s &\triangleq \{\text{target is perceivable from } s\} \\ \bar{O}_k^s &\triangleq \{\text{target is unperceivable from } s\} \end{aligned}$$

When there are m_k^s validated measurements at time k, the intersection of these events with the classical data association events involved in the PDAF formalism [4]

$$\begin{aligned} \theta_i^s(k) &\triangleq \{\mathbf{z}^s_{j_s}(k) \text{ comes from target}\} \\ \theta_0^s(k) &\triangleq \{\text{none of } \mathbf{z}^s_{j_s}(k) \text{ comes from target}\} \end{aligned}$$

defines a new set of integrated association events

$$\begin{aligned} \mathcal{E}^s_{-j_s}(k) &\triangleq \bar{O}_k^s \cap \theta^s_{j_s}(k) \qquad j_s = 1, \dots, m_k^s \\ \mathcal{E}^s_{\bar{0}}(k) &\triangleq \bar{O}_k^s \cap \theta^s_0(k) \\ \mathcal{E}^s_{0}(k) &\triangleq O_k^s \cap \theta^s_0(k) \\ \mathcal{E}^s_{j_s}(k) &\triangleq O_k^s \cap \theta^s_{j_s}(k) \qquad j_s = 1, \dots, m_k^s \end{aligned}$$

Since any target measurement cannot arise without target perceivability, events $\mathcal{E}^s_{-j_s}(k), j_s = 1, \dots, m_k^s$ are impossible and we have $P\{\mathcal{E}_{-i}(k)|.\} = P\{\emptyset|.\} = 0$. Only events $\mathcal{E}^s_{\bar{0}}(k)$, $\mathcal{E}^s_0(k)$ and $\mathcal{E}^s_{j_s}(k)$ $(j_s = 1, \dots, m_k^s)$ may have a non null probability to occur. The development of a new PDAF (called IPDAF) based on these integrated association events yields the following updating equations (see [14, 15] for complete derivation) which are valid for $m_k^s \geq 0$:

$$\hat{\mathbf{x}}^s(k|k) = \sum_{j_s=\bar{0},0}^{m_k^s} \beta^s_{j_s}(k)\hat{\mathbf{x}}^s_{j_s}(k|k) \tag{3}$$

$$\mathbf{P}^s(k|k) = \Big[\sum_{j_s=\bar{0},0}^{m_k^s} \beta^s_{j_s}(k)\mathbf{P}^s_{j_s}(k|k)\Big] - \hat{\mathbf{x}}^s(k|k)\hat{\mathbf{x}}^s(k|k)' + \sum_{j_s=\bar{0},0}^{m_k^s} \beta^s_{j_s}(k)\hat{\mathbf{x}}^s_{j_s}(k|k)\hat{\mathbf{x}}^s_{j_s}(k|k)' \tag{4}$$

where the conditional estimates and their covariances are

$$\hat{\mathbf{x}}^s_{\bar{0}}(k|k) = \hat{\mathbf{x}}^s(k|k-1) \tag{5}$$
$$\hat{\mathbf{x}}^s_0(k|k) = \hat{\mathbf{x}}^s(k|k-1) \tag{6}$$
$$\hat{\mathbf{x}}^s_{j_s}(k|k) = \hat{\mathbf{x}}^s(k|k-1) + \mathbf{K}^s(k)\tilde{\mathbf{z}}^s_{j_s}(k) \tag{7}$$
$$\mathbf{P}^s_{\bar{0}}(k|k) = \mathbf{P}^s(k|k-1) \tag{8}$$
$$\mathbf{P}^s_0(k|k) = [\mathbf{I} + q_0^s\mathbf{K}^s(k)\mathbf{H}^s(k)]\mathbf{P}^s(k|k-1) \tag{9}$$
$$\mathbf{P}^s_{j_s}(k|k) = [\mathbf{I} - \mathbf{K}^s(k)\mathbf{H}^s(k)]\mathbf{P}^s(k|k-1) \tag{10}$$

with the following computations [14, 15, 16]

$$\begin{aligned} q_0^s &\triangleq \frac{P_d^s(P_g^s - P_{gg}^s)}{1 - P_d^s P_g^s} \\ P_g^s &\triangleq P\{\chi^2_{n_{z^s}} \leq \gamma\} \\ P_{gg}^s &\triangleq P\{\chi^2_{n_{z^s}+2} \leq \gamma\} \\ \mathbf{S}^s(k) &= \mathbf{H}^s(k)\mathbf{P}^s(k|k-1)\mathbf{H}^s(k) + \mathbf{R}^s(k) \\ \mathbf{K}^s(k) &= \mathbf{P}^s(k|k-1)\mathbf{H}^s(k)'[\mathbf{S}^s(k)]^{-1} \\ \hat{\mathbf{z}}^s(k|k-1) &= \mathbf{H}^s(k)\hat{\mathbf{x}}^s(k|k-1) \end{aligned}$$

$$\tilde{\mathbf{z}}^s_{j_s}(k) = \mathbf{z}^s_{j_s}(k) - \hat{\mathbf{z}}^s(k|k-1)$$
$$\tilde{\mathbf{z}}^s(k) = \sum_{j_s=1}^{m_k^s} \beta^s_{j_s}(k)\tilde{\mathbf{z}}^s_{j_s}(k)$$

The integrated a posteriori data association probabilities $\beta_{j_s}(k) \triangleq P\{\mathcal{E}_{j_s}(k)|\mathbf{Z}^s(k), m_k^s, \mathbf{Z}^{k-1,s}\}$ $(j_s = \bar{0}, 0, \ldots, m_k^s)$ taking into account the target perceivability are given by

- when $m_k^s = 0$,

$$\beta^s_{\bar{0}}(k) = 1 - P^{O^s}_{k|k-1,0} \quad (11)$$
$$\beta^s_0(k) = P^{O^s}_{k|k-1,0} \quad (12)$$

- when $m_k^s > 0$,

$$\beta^s_{j_s}(k) = \frac{1}{c^s} e_{j_s}(k) P^{O^s}_{k|k-1,m_k^s} \quad (13)$$
$$\beta^s_0(k) = \frac{1}{c^s} b^s_0(k) P^{O^s}_{k|k-1,m_k^s} \quad (14)$$
$$\beta^s_{\bar{0}}(k) = \frac{1}{c^s} b^s_{\bar{0}}(k)(1 - P^{O^s}_{k|k-1,m_k^s}) \quad (15)$$

where c^s is a normalization constant and

$$e_{j_s}(k) \triangleq \frac{1}{P_g^s}\mathcal{N}[\tilde{\mathbf{z}}^s_{j_s}(k); 0; \mathbf{S}^s(k)]$$
$$b^s_0(k) \triangleq \frac{m_k^s}{V_k^s}\frac{1 - P_d^s P_g^s}{P_d^s P_g^s}\xi_k^s$$
$$b^s_{\bar{0}}(k) \triangleq \frac{m_k^s}{V_k^s}\frac{1}{P_d^s P_g^s}\left[P_d^s P_g^s + (1 - P_d^s P_g^s)\xi_k^s\right]$$

V_k^s is the volume of the measurement validation gate for sensor s [4, 5] and ξ_k^s, $\mu_F(.)$ are defined as

$$\xi_k^s \triangleq \frac{\mu_F(m_k^s)}{\mu_F(m_k^s - 1)}$$
$$\mu_F(.) \triangleq \text{pmf of number of false alarms in } V_k^s$$

If a Poisson model with clutter density λ^s for μ_F is assumed, the predicted and updated conditional and unconditional target perceivability probabilities ($P^{O^s}_{k|k-1} \triangleq P\{O_k^s|\mathbf{Z}^{k-1,s}\}$ and $P^{O^s}_{k|k} \triangleq P\{O_k^s|\mathbf{Z}^{k,s}\}$) can be expressed as [14, 15, 16]

$$P^{O^s}_{k|k-1,m_k^s} = \frac{(1 - \epsilon_k^s)P^{O^s}_{k|k-1}}{1 - \epsilon_k^s P^{O^s}_{k|k-1}} \quad (16)$$

with

$$\epsilon_k^s \triangleq \begin{cases} P_d^s P_g^s & m_k^s = 0 \\ P_d^s P_g^s(1 - \frac{m_k^s}{\lambda^s V_k^s}) & m_k^s \neq 0 \end{cases} \quad (17)$$

and

$$P^{O^s}_{k|k-1} = \pi^s_{11}P^{O^s}_{k-1|k-1} + \pi^s_{21}(1 - P^{O^s}_{k-1|k-1}) \quad (18)$$
$$P^{O^s}_{k|k} = \frac{(1 - \phi_k^s)P^{O^s}_{k|k-1}}{1 - \phi_k^s P^{O^s}_{k|k-1}} \quad (19)$$

$$\phi_k^s \triangleq \begin{cases} P_d^s P_g^s & m_k^s = 0 \\ P_d^s P_g^s(1 - \frac{1}{\lambda^s}\sum_{j_s=1}^{m_k^s} e_{j_s}) & m_k^s \neq 0 \end{cases} \quad (20)$$

Hence $P^{O^s}_{k|k-1}$ and $P^{O^s}_{k|k}$ can be computed on-line recursively as soon as the *design parameters* $\pi^s_{11} \triangleq P\{O_k^s|O_{k-1}^s\}$, $\pi^s_{21} \triangleq P\{O_k^s|\bar{O}_{k-1}^s\}$ and $P^{O^s}_{1|0}$ have been set. In practice, the clutter density λ^s is usually unknown. To implement the IPDAF, we have to replace λ^s by its estimation based on the Bayesian (conditional mean) estimation, the maximum likelihood method or the least squares method recently developed in [15, 19]. Theoretical investigations on design of IPDAF trackers for perceivability probability enhancement can be found in [17].

Finally with some elementary algebra $\mathbf{P}^s(k|k)$ given by (4) can take the following forms depending on m_k^s

- when $m_k^s = 0$, $\mathbf{P}^s(k|k) =$

$$[\mathbf{I} + q_0^s P^{O^s}_{k|k-1,0}\mathbf{K}^s(k)\mathbf{H}^s(k)]\mathbf{P}^s(k|k-1)$$

- when $m_k^s > 0$, $\mathbf{P}^s(k|k) =$

$$\begin{aligned}&\beta^s_{\bar{0}}(k)\mathbf{P}^s(k|k-1)\\ &+ \beta^s_0(k)[\mathbf{I} + q_0^s\mathbf{K}^s(k)\mathbf{H}^s(k)]\mathbf{P}^s(k|k-1)\\ &+ (1 - \beta^s_{\bar{0}}(k) - \beta^s_0(k))\mathbf{P}^{c,s}(k|k) + \tilde{\mathbf{P}}^s(k)\end{aligned}$$

with

$$\mathbf{P}^{c,s}(k|k) = [\mathbf{I} - \mathbf{K}^s(k)\mathbf{H}^s(k)]\mathbf{P}^s(k|k-1)$$
$$\tilde{\mathbf{P}}^s(k) = \mathbf{K}^s(k)[\sum_{j_s=1}^{m_k^s}\beta^s_{j_s}(k)\tilde{\mathbf{z}}^s_{j_s}(k)\tilde{\mathbf{z}}^s_{j_s}(k)' - \tilde{\mathbf{z}}^s(k)\tilde{\mathbf{z}}^s(k)']\mathbf{K}^s(k)'$$

The local state prediction is done according to classical prediction equations, i.e.

$$\hat{\mathbf{x}}^s(k+1|k) = \mathbf{F}(k)\hat{\mathbf{x}}^s(k|k)$$
$$\mathbf{P}^s(k+1|k) = \mathbf{F}(k)\mathbf{P}^s(k|k)\mathbf{F}'(k) + \mathbf{Q}(k)$$

4 The Distributed IPDAF

Given the local statistics delivered by s local IPDAF of a s-node sensor network[1], we are now looking for the solution of the distributed estimation problem in order to retrieve the optimal global target state estimate and its covariance which are given by [2]

$$\begin{aligned}\hat{\mathbf{x}}(k|k) &= E[\mathbf{x}(k)|\mathbf{Z}^{1,k}, \dots, \mathbf{Z}^{s,k}] \\ &= \sum_{j_1=\bar{0},0}^{m_k^1} \cdots \sum_{j_s=\bar{0},0}^{m_k^s} \beta_{j_1,j_s}(k)\hat{\mathbf{x}}_{j_1,j_s}(k|k) \quad (21)\end{aligned}$$

with

$$\begin{aligned}\beta_{j_1,j_s}(k) &\triangleq P(\mathcal{E}^1_{j_1}(k), \dots, \mathcal{E}^s_{j_s}(k)|\mathbf{Z}^{1,k}, \dots, \mathbf{Z}^{s,k}) \\ \hat{\mathbf{x}}_{j_1,j_s}(k|k) &\triangleq E[\mathbf{x}(k)|\mathbf{Z}^{1,k}, \mathcal{E}^1_{j_1}(k), \dots, \mathbf{Z}^{s,k}, \mathcal{E}^s_{j_s}(k)]\end{aligned}$$

and

$$\begin{aligned}\mathbf{P}(k|k) &= \sum_{j_1=\bar{0},0}^{m_k^1} \sum_{j_s=\bar{0},0}^{m_k^s} \beta_{j_1,j_s}(k)\mathbf{P}_{j_1,j_s}(k|k) \\ &+ \sum_{j_1=\bar{0},0}^{m_k^1} \sum_{j_s=\bar{0},0}^{m_k^s} \beta_{j_1,j_s}(k)\big[\hat{\mathbf{x}}_{j_1,j_s}(k|k)\hat{\mathbf{x}}_{j_1,j_s}(k|k)' \\ &\qquad - \hat{\mathbf{x}}(k|k)\hat{\mathbf{x}}(k|k)'\big]\end{aligned}$$

These previous equations are always valid whatever the values of $m_k^1, \dots, m_k^s$ are. If there is no validated measurement for a given node at a given time, the corresponding summation must be only computed from $\bar{0}$ up to 0.

If we assume the measurement errors from sensors independent, the joint conditional estimates with their covariances can be obtained from the optimal distributed fusion equations of Chong [9, 8, 2, 6].

$$\begin{aligned}\hat{\mathbf{x}}_{j_1,j_s}(k|k) = \mathbf{P}_{j_1,j_s}(k|k)\Big[&\mathbf{P}(k|k-1)^{-1}\hat{\mathbf{x}}(k|k-1) \\ &+ \sum_{i=1}^{s} \mathbf{P}^i_{j_i}(k|k)^{-1}\hat{\mathbf{x}}^i_{j_i}(k|k) \\ &- \sum_{i=1}^{s} \mathbf{P}^i(k|k-1)^{-1}\hat{\mathbf{x}}^i(k|k-1)\Big]\end{aligned} \quad (22)$$

$$\begin{aligned}\mathbf{P}_{j_1,j_s}{}^{-1}(k|k) =& \mathbf{P}(k|k-1)^{-1} + \sum_{i=1}^{s} \mathbf{P}^i_{j_i}(k|k)^{-1} \\ & - \sum_{i=1}^{s} \mathbf{P}^i(k|k-1))^{-1}\end{aligned} \quad (23)$$

When all nodes communicate every scan the global and local prior estimates are the same (i.e. $\hat{\mathbf{x}}^i(k|k-1) = \hat{\mathbf{x}}(k|k-1)$ and $\mathbf{P}^i(k|k-1) = \mathbf{P}(k|k-1)$) and then eqs. (22) and (23) will reduce to

$$\begin{aligned}\hat{\mathbf{x}}_{j_1,j_s}(k|k) = \mathbf{P}_{j_1,j_s}(k|k)\Big[&[\sum_{i=1}^{s} \mathbf{P}^i_{j_i}(k|k)^{-1}\hat{\mathbf{x}}^i_{j_i}(k|k)] \\ &- (s-1)\mathbf{P}(k|k-1)^{-1}\hat{\mathbf{x}}(k|k-1)\Big]\end{aligned} \quad (24)$$

$$\begin{aligned}\mathbf{P}_{j_1,j_s}{}^{-1}(k|k) = &[\sum_{i=1}^{s} \mathbf{P}^i_{j_i}(k|k)^{-1}] \\ &- (s-1)\mathbf{P}(k|k-1)^{-1}\end{aligned} \quad (25)$$

The derivation of $\beta_{j_1,j_s}(k)$ is quite complicated and will not be detailed here. We refer the reader to [8] for a complete derivation. Assuming the independence between sensor measurements and between events $\mathcal{E}^1_{j_1}(k), \dots, \mathcal{E}^s_{j_s}(k)$ given the target state, then the final expression for $\beta_{j_1,j_s}(k)$ is

$$\beta_{j_1,j_s}(k) = \frac{1}{c}\gamma(\mathcal{E}^1_{j_1}(k), \dots, \mathcal{E}^s_{j_s}(k)) \prod_{i=1}^{s} \beta^i_{j_i}(k) \quad (26)$$

where c is a normalization constant such that

$$\sum_{j_1=\bar{0},0}^{m_k^1} \cdots \sum_{j_s=\bar{0},0}^{m_k^s} \beta_{j_1,j_s}(k) = 1$$

and where the correlation factor $\gamma(\mathcal{E}^1_{j_1}(k), \dots, \mathcal{E}^s_{j_s}(k))$ is given by

$$\int p(\mathbf{x}(k)|\mathbf{Z}^{1,k-1}, \mathbf{Z}^{s,k-1}) \frac{\prod_{i=1}^{s} p(\mathbf{x}(k)|\mathcal{E}^i_{j_i}(k), \mathbf{Z}^{i,k})}{\prod_{i=1}^{s} p(\mathbf{x}(k)|\mathbf{Z}^{i,k-1})} d\mathbf{x}$$

Using the gaussian distribution approximation and moment matching method, it can be shown

[1] s represents now the total number of sensors in the DSN instead of typical sensor index as in previous section

[2] due to space limitation, notation j_1, j_s must actually be read $j_1, \dots, j_s$ and sometimes $\mathbf{Z}^{1,k}, \mathbf{Z}^{s,k}$ as $\mathbf{Z}^{1,k}, \dots, \mathbf{Z}^{s,k}$

that $\gamma(\mathcal{E}^1_{j_1}(k),\ldots,\mathcal{E}^s_{j_s}(k))$ can be approximated by

$$\sqrt{\frac{|\mathbf{P}_{j_1,j_s}(k|k)|\prod_{i=1}^s|\mathbf{P}^i(k|k-1)|}{|\mathbf{P}(k|k-1)|\prod_{i=1}^s|\mathbf{P}^i_{j_i}(k|k)|}}e^{-\frac{1}{2}D_{j_1,j_s}}$$

with

$$\begin{aligned}D_{j_1,j_s} \triangleq & \Big[\sum_{i=1}^s \hat{\mathbf{x}}^i_{j_i}(k|k)'\mathbf{P}^i_{j_i}(k|k)^{-1}\hat{\mathbf{x}}^i_{j_i}(k|k) \\ & -\hat{\mathbf{x}}^i(k|k-1)'\mathbf{P}^i(k|k-1)^{-1}\hat{\mathbf{x}}^i(k|k-1)\Big] \\ & +\hat{\mathbf{x}}(k|k-1)'\mathbf{P}(k|k-1)^{-1}\hat{\mathbf{x}}(k|k-1) \\ & -\hat{\mathbf{x}}_{j_1,j_s}(k|k)'\mathbf{P}_{j_1,j_s}(k|k)^{-1}\hat{\mathbf{x}}_{j_1,j_s}(k|k)\end{aligned}$$

When all nodes communicate every scan, $\gamma(\mathcal{E}^1_{j_1}(k),\ldots,\mathcal{E}^s_{j_s}(k))$ will reduce to

$$\sqrt{\frac{|\mathbf{P}_{j_1,j_s}(k|k)||\mathbf{P}(k|k-1)|^{s-1}}{\prod_{i=1}^s|\mathbf{P}^i_{j_i}(k|k)|}}e^{-\frac{1}{2}D_{j_1,j_s}}$$

with

$$\begin{aligned}D_{j_1,j_s} \triangleq & \Big[\sum_{i=1}^s \hat{\mathbf{x}}^i_{j_i}(k|k)'\mathbf{P}^i_{j_i}(k|k)^{-1}\hat{\mathbf{x}}^i_{j_i}(k|k)\Big] \\ & -(s-1)\hat{\mathbf{x}}(k|k-1)'\mathbf{P}(k|k-1)^{-1}\hat{\mathbf{x}}(k|k-1) \\ & -\hat{\mathbf{x}}_{j_1,j_s}(k|k)'\mathbf{P}_{j_1,j_s}(k|k)^{-1}\hat{\mathbf{x}}_{j_1,j_s}(k|k)\end{aligned}$$

where $\hat{\mathbf{x}}_{j_1,j_s}(k|k)$ and $\mathbf{P}_{j_1,j_s}{}^{-1}(k|k)$ are obtained from (24) and (25) respectively.

5 Simulation results

A two-dimensional single ground-target tracking problem is considered here. The target is assumed to move on a road in a town with (nearly) constant velocity of 36 km/h during 110 s from crossroad A towards the crossroad C as on figure 1. Only three buildings $B1$, $B2$ and $B3$ have been simulated in our scenario. The target dynamic model (i.e. piecewise constant white acceleration model) with discretization over time interval of length $T = 1s$ is [5]

$$\mathbf{x}(k+1) = \mathbf{F}\mathbf{x}(k) + \mathbf{G}\mathbf{v}(k)$$

where $\mathbf{x}(k) = [x\ \dot{x}\ y\ \dot{y}]'$ is the target state vector at time k and $\mathbf{F}$ and $\mathbf{G}$ are given by

$$\mathbf{F} = \begin{bmatrix}1 & T & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 1 & T\\ 0 & 0 & 0 & 1\end{bmatrix} \qquad \mathbf{G} = \begin{bmatrix}T^2/2 & 0\\ T & 0\\ 0 & T^2/2\\ 0 & T\end{bmatrix}$$

The process noise $\mathbf{v}(k)$ representing the acceleration during one period is a zero-mean Gaussian white noise having covariance $\mathbf{Q}_v = diag(q_v, q_v)$ with $q_v = (0.001m/s^2)^2$. The magnitude of the process noise has been chosen very low in order to force the target to move on the segment $[A;C]$ (middle of the road). The true initial target state is assumed to be $\mathbf{x}(0) = [-800\text{ m } 10\text{ m/s } -450\text{ m } 0\text{ m/s}]'$.

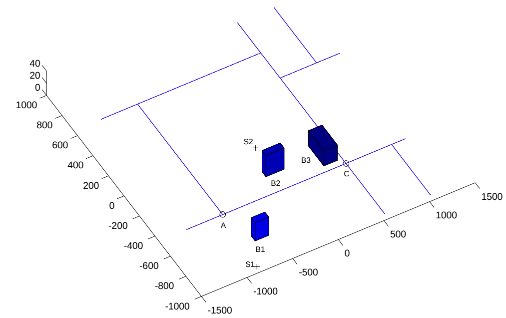

Figure 1: Urban environment scenario

We have considered a 2-nodes DSN with full communication at every scan. The sensor $S1$ is located at position (−850 m, −950 m) and $S2$ at (−100 m, −50 m). It is assumed that only position measurements are available, i.e.

$$\mathbf{z}^i(k) = \mathbf{H}\mathbf{x}(k) + \mathbf{w}^i(k) \qquad i = 1,2$$

with

$$\mathbf{H} = \begin{bmatrix}1 & 0 & 0 & 0\\ 0 & 0 & 1 & 0\end{bmatrix}$$

Figure 2 shows the line of sight between sensors and the true target position for a given realization of the process noise. On average for our scenario, the target is occulted by building $B1$ for sensor $S1$ during period [25s; 72s] and by $B2$ for sensor $S2$ during period [50s; 92s]. Thus during period [50s; 72s] the target is occulted for both sensors.

Both sensors have same measurement precision. The standard deviation of measurement errors are 5 meters on x and y coordinates. The detection probabilities for both sensors are equal to 0.7 and the false alarm rates are both equal to $\lambda = 0.0003FA/m^2$. The initial state estimate for both sensors is estimated using the so-called two-point differencing technique (TPD) [5, 6] (see also [20] for recent advances).

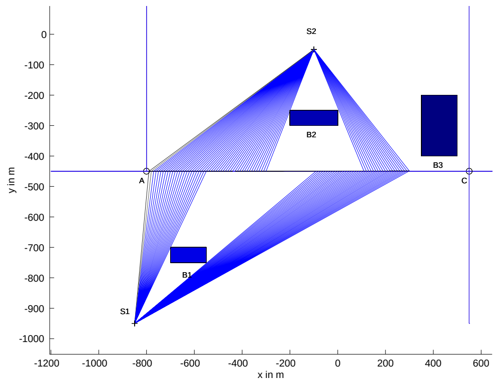

Figure 2: Perceivability scenario (top view)

At each scan, each node will process its own set of sensor measurements first using local IPDAF, then will send its local processed results to the fusion node. After receiving the information from local nodes, the fusion node will use the the distributed fusion algorithm presented at the end of section 4 to construct the global estimate and will send the results back to each local node at every sampling time. Both local IPDAF use the same set of design parameters ($P_g = 0.99$, $\pi_{11} = 0.988$, $\pi_{21} = 0.05$ and $P^O_{1|0} = 0.5$) and the true value λ for clutter density.

Simulations were carried out with 50 Monte Carlo runs. The results of successful runs for decentralized trackers (without fusion) are plotted on figures 3 and 4. A successful run is defined when the estimated target position is within 30 m of the true target position for the last three scans [7]. Figures 5 and 6 show the averaged performances of the successful runs for the decentralized case. We can observe from figure 5 and figure 6 that the target perceivability probabilities estimated by the local IPDAF fit well their true values even when the perceivability mode is switching. Obviously in nominal mode (for $k > 20s$), the rms position errors increase with time when the target becomes unperceivable by the sensors. The maximum of rms errors are obtained for k around 72 s and 92 s. These instants correspond to the end of the unperceivability period for each sensor. For the decentralized case, out of 50 runs, sensor 1 alone and sensor 2 alone only track the occulted target successfully in 29 and 41 runs, respectively.

Figures 7 and 8 show the results obtained with the distributed IPDAF (distributed communication scheme at every scan). According to the results plotted on the figures, the distributed IPDAF performs better than the single sensor configurations. In nominal mode, the maximum rms position error is now obtained for $k = 72$ s which corresponds to the end of the period where the target is unperceivable by both sensors simultaneously which makes sense with the theory. In such case, the DIPDAF sucessfully tracks the target in 48 out of 50 runs. Note also that the quality of estimation using both sensors in terms of mean square error and in terms of target perceivability estimation is significantly better than with the decentralized scheme. In our simulations the averaged number of false alarms per gate was around 0.5. The simulations shows the usefulness and the improvement of DIPDAF with respect to decentralized schemes for tracking an occulted ground-target in an urban cluttered environment.

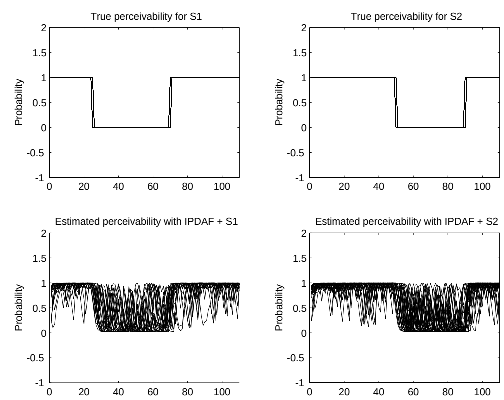

Figure 3: Estimated perceivability probabilities (decentralized communication case)

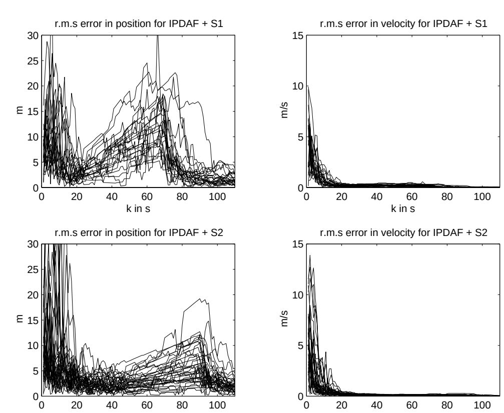

Figure 4: R.M.S. errors for successful runs (decentralized communication case)

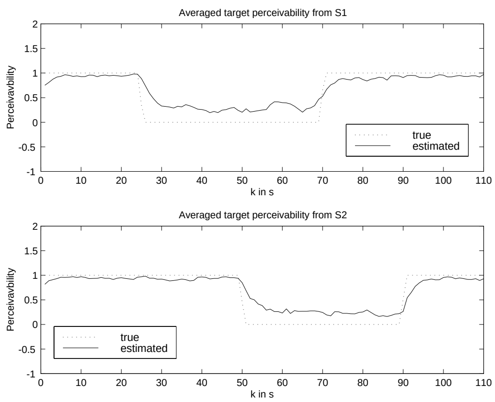

Figure 5: Averaged perceivability probabilities (decentralized communication case)

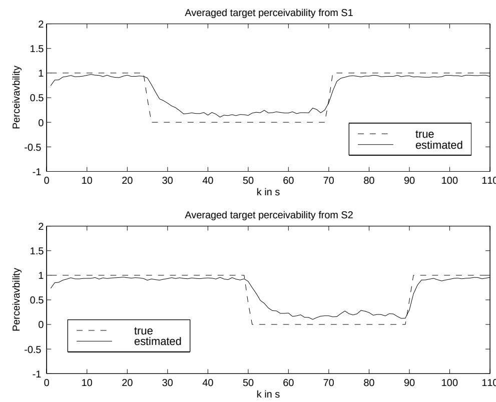

Figure 7: Averaged perceivability probabilities (distributed communication case)

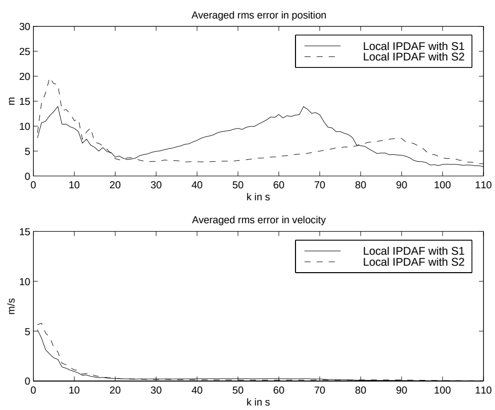

Figure 6: Averaged R.M.S. errors for successful runs (decentralized communication case)

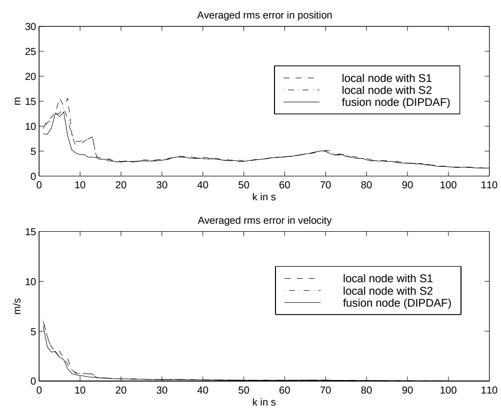

Figure 8: Averaged R.M.S. errors for successful runs (distributed communication case)

6 Conclusion

From a new formulation of IPDAF based on a recent method for target perceivability probability estimation and by following the theoretical approach of Chang and al. [8, 11, 21], a distributed version of IPDAF (called DIPDAF) has been proposed here (with implicit assumption of lossless communication of sufficient statistics). This algorithm takes into account the information fusion in a distributed sensor network. This new DIPDAF is fully coherent and intuitively appealing with the Distributed PDAF formulation [2] as soon as the target perceivability probabilities for each sensor becomes unitary. This filter has been successfully implemented for tracking a ground-target occasionally occulted in a cluttered urban environment on a simple 2-nodes 2D scenario. Extension of this new tracker for tracking maneuvering target with or without different local observation models could also be developed by taking into account methodology described in previous works [7] and [1, 3]. Another extension of this algorithm for multi-target tracking based on the IJPDAF developed in [13] is under investigations.

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