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DISTRIBUTED MULTITARGET TRACKING WITH RANGE-DOPPLER SENSORS

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ABSTRACT

The paper applies a recently developed Consensus Gaussian Mixture - Cardinalized Probability Hypothesis Density (CGM-CPHD) filter to distributed multitarget tracking with range and/or Doppler sensors. It is demonstrated via simulation results on realistic scenarios that the use of Doppler measurements provides a significant tracking performance improvement with respect to using low-accuracy range measurements only. On the other hand, effective distributed Doppler-only multitarget tracking is still an open issue to be investigated.

***Index Terms*—** Multitarget tracking; distributed tracking; sensor networks; Doppler measurements.

1. INTRODUCTION

Doppler-shift measurements are easy to obtain and can provide valuable information, if properly exploited, for target tracking purposes. In many practical situations, it is possible to deploy over the area of interest several units equipped with on-board capabilities of receiving target echoes, measuring the Doppler-shift and/or the time-of-arrival of such echoes (and hence the range rate and/or range of the echoing targets), exchanging data with neighboring units as well as processing local data so as to setup a low-cost and passive distributed surveillance network. The objective is that each node of the network be able to gain the global situation awareness (i.e. knowledge of the number of moving targets and their position, velocity, etc.) in a fully distributed and scalable way. To this end, in [1] an efficient distributed consensus-based multitarget multisensor tracker, named CGM-CPHD (Consensus Gaussian-Mixture Cardinalized Probability Hypothesis Density) filter, has been developed and its performance has been thoroughly analysed with heterogeneous surveillance networks made up of angle-only and/or range-only sensors. The aim of the present paper was to investigate whether CGM-CPHD can satisfactorily cope with the more difficult Doppler-only tracking problem. In this respect, the case study considered in this work, involving a surveillance network with range and/or Doppler sensors, allows to conclude that (1) the use of Doppler measurements provides indeed a significant tracking performance improvement with respect to using low-accuracy range measurements only but (2) Doppler-only multitarget tracking is still an open issue to be investigated.

2. DISTRIBUTED MULTITARGET TRACKING (DMTT)

2.1. Network model

It is assumed that the surveillance network used for multi-target tracking consists of heterogeneous and geographically dispersed nodes with processing, communication and sensing capabilities. More specifically, each node can process local data as well as exchange data with the neighbors and can get measurements of kinematic variables (e.g., angles, distances and/or Doppler shifts) relative to targets moving in the surrounding environment. It is also assumed that the netwok has no *central fusion node* and that its nodes are unaware of the overall network topology. From a mathematical point of view, the network is represented by a directed graph $\mathcal{G} = (\mathcal{N}, \mathcal{A})$ where $\mathcal{N}$ is the set of nodes and $\mathcal{A} \subseteq \mathcal{N} \times \mathcal{N}$ the set of arcs, representing links (connections). In particular, (i, j) belongs to $\mathcal{A}$ if node j can receive data from node i. For each node $j \in \mathcal{N}$, $\mathcal{N}^j \triangleq \{i \in \mathcal{N} : (i, j) \in \mathcal{A}\}$ denotes its set of neighbors, i.e. the set of nodes from which node j can receive data. By definition, $(j, j) \in \mathcal{A}$ for any node $j \in \mathcal{N}$ and, hence, $j \in \mathcal{N}^j$ for all j. The total number of nodes in the network will be denoted by $N \triangleq |\mathcal{N}|$, the cardinality of $\mathcal{N}$.

2.2. Representation of multitarget information

The nodes of the surveillance network need to locally update, exchange and fuse information on the number of targets in the scene as well as their kinematic (position-velocity) states. For computational and communication efficiency, a parsimonious representation of such a multitarget information is advocated. To this end, a possible representation is made up of:

1. the cardinality distribution $p(n)$ defined, for any integer $n \geq 0$, as the probability that there are n targets in the scene;

2. the intensity function $d(\mathbf{x})$, also called Probability Hypothesis Density (PHD) [2, 3], that quantifies the density of targets at the state $\mathbf{x}$.

Without loss of generality, the PHD can be expressed as $d(\mathbf{x}) = \overline{n}s(\mathbf{x})$ where $\overline{n} \stackrel{\triangle}{=} \sum_n np(n)$ is the expected number of targets and $s(\cdot)$ is the location function such that $\int s(\mathbf{x})d\mathbf{x} = 1$. In this paper, following [1], multitarget information is represented by the cardinality distribution $p(\cdot)$ and by the location function $s(\cdot)$ that are jointly referred to as the Cardinalized PHD (CPHD) [4]. From the CPHD, the estimated number of targets is typically obtained from the cardinality distribution according to the MAP criterion as $\hat{n} = max_n \, p(n)$ while the target state estimates are extracted as peaks of the location function $s(\cdot)$. Notice that both $p(\cdot)$ and $s(\cdot)$ are, in principle, infinite-dimensional so that, for implementation purposes, finitely-parameterized representations of both need to be adopted. For the cardinality distribution $p(n)$, it is enough to assume a sufficiently large maximum number of targets n_{max} in the scene and restrict $p(\cdot)$ to the finite subset of integers $\{0, 1, \ldots, n_{max}\}$. Conversely, for the location function, two representations based on the *particle* or *Monte Carlo* (MC) or, respectively, *Gaussian Mixture* (GM) approaches are most commonly adopted. In this work, the GM approach is followed by expressing location functions as linear combinations of Gaussian components, i.e.,

$$s(\mathbf{x}) \; = \; \sum_{j=1}^{N_G} \alpha_j \, \mathcal{N}\left(\mathbf{x}; \hat{\mathbf{x}}_j, \mathbf{P}_j\right)$$

The reason of this choice is that for DMTT over a sensor network, typically characterized by limited processing power and energy resources of the individual nodes, it is of paramount importance to reduce as much as possible local (in-node) computations and inter-node data communication. In this respect, the GM approach is certainly more parsimonious (usually the number of Gaussian components involved is orders of magnitude lower than the number of particles required for a reasonable tracking performance) and hence preferable. In summary, multitarget information is compactly characterized by the following quantities

$$\{p(n)\}_{n=0}^{n_{max}} \, , \quad \{(\alpha_j, \hat{\mathbf{x}}_j, \mathbf{P}_j)\}_{j=1}^{N_G}$$

2.3. Local update of multitarget information

In each node i of the network, the local CPHD, i.e. the pair $\left(p^i(\cdot), s^i(\cdot)\right)$, is updated in time exploiting the multitarget dynamics (which accounts for target motion, birth and death) and then corrected with the current local measurements exploiting the measurement model (which accounts for true measurement and clutter generation, missed detections). This local update can be carried out by the CPHD filter [4]. The resulting CPHD recursions (prediction and correction) are as follows

Prediction (1)

$$p_{t|t-1}(n) = \sum_{j=0}^{n} p_b(n-j) \; \pi_{t|t-1}(j)$$

$$d_{t|t-1}(\mathbf{x}) = d_{b,t}(\mathbf{x}) + \int \boldsymbol{\varphi}_{t|t-1}(\mathbf{x}|\boldsymbol{\xi}) P_{s,t-1}(\boldsymbol{\xi}) d_{t-1|t-1}(\boldsymbol{\xi}) d\boldsymbol{\xi}$$

Correction (2)

$$p_{t|t}(n) = \frac{\mathcal{L}_t^0\left(d_{t|t-1}(\cdot), \mathcal{Y}_t, n\right) \; p_{t|t-1}(n)}{\displaystyle\sum_{i=0}^{\infty} \mathcal{L}_t^0\left(d_{t|t-1}(\cdot), \mathcal{Y}_t, i\right) \; p_{t|t-1}(i)}$$

$$d_{t|t}(\mathbf{x}) = \mathcal{L}_{\mathcal{Y}_t}(\mathbf{x}) \; d_{t|t-1}(\mathbf{x})$$

where: $p_{b,t}(\cdot)$ is the assumed birth cardinality distribution; $P_{s,t-1}(\cdot)$ is the assumed survival probability; $\pi_{t|t-1}(\cdot)$ is the cardinality distribution of survived targets, given by
$\pi_{t|t-1}(j) \; = \; \sum_{h=j}^{\infty} \left(\begin{array}{c} h \\ j \end{array}\right) P_{s,t}^{j} \; (1 - P_{s,t})^{h-j} \; p_{t-1|t-1}(h);$
$d_{b,t}(\cdot)$ is the assumed PHD function of new-born targets; $\boldsymbol{\varphi}_{t|t-1}(\mathbf{x}|\boldsymbol{\xi})$ is the state transition PDF associated to the single target dynamics $\mathbf{x} = \mathbf{f}_{t-1}(\boldsymbol{\xi}, \mathbf{w})$; the generalized likelihood functions $\mathcal{L}_t^0(\cdot, \cdot, \cdot)$ and $\mathcal{L}_{\mathcal{Y}_t}(\cdot)$ have cumbersome expressions which can be found in [4].

2.4. Fusion of multitarget information

The local CPHDs $\left(p^i, s^i\right)$ of the various nodes $i \in \mathcal{N}$ should be consistently fused into a sort of average CPHD $(\overline{p}, \overline{s})$. In [1] an information-theoretic, Kullback-Leibler, average of multitarget distributions has been defined and it has been shown that this average actually coincides with the Generalized Covariance Intersection (GCI) fusion [5, 6]. The resulting averaged (fused) CPHD is given by

$$\overline{s}(\mathbf{x}) = \frac{\left[\prod_i s^i(\mathbf{x})\right]^{\frac{1}{N}}}{\int \left[\prod_i s^i(\mathbf{x})\right]^{\frac{1}{N}} d\mathbf{x}} \qquad (3)$$

$$\overline{p}(n) = \frac{\left[\prod_i p^i(n)\right]^{\frac{1}{N}} \left\{\int \left[\prod_i s^i(\mathbf{x})\right]^{\frac{1}{N}} d\mathbf{x}\right\}^n}{\sum_{m=0}^{\infty} \left[\prod_i p^i(m)\right]^{\frac{1}{N}} \left\{\int \left[\prod_i s^i(\mathbf{x})\right]^{\frac{1}{N}} d\mathbf{x}\right\}^m} \tag{4}$$

Notice that the fused location function $\overline{s}(\cdot)$ is the geometric mean of the node location functions $s^i(\cdot)$ while the fused cardinality $\overline{p}(\cdot)$ is obtained by (4) which also involves the node location functions besides the node cardinality distributions. In [1] it has been shown that the geometric mean of Gaussian mixtures (GMs) is no longer a GM so that, in order to preserve the GM form of the location function, a suitable approximation has been devised. Please refer to [1] for the details of the approximate fusion of GMs; it is worth to point out that such an approximate fusion of two GMs $s^a(\cdot)$ and $s^b(\cdot)$, with N_G^a and respectively N_G^b components, produces a fused GM $s(\cdot)$ with $N_G^a N_G^b$ components, one for each pair of Gaussian components of the fusing GMs.

3. SCALABLE MULTITARGET FUSION VIA CONSENSUS

In order to carry out the collective fusion (3)-(4) in a fully distributed and scalable way, a consensus approach can be exploited [7]. The idea of consensus is the following: to perform fusion of the CPHDs $\left(p^i, s^i\right)$ over the whole network, regional fusions are iteratively carried out in each node i over the sub-network of neighbors $\mathcal{N}^i$. The generic CPHD consensus iteration can be summarized as follows:

$$s_{\ell+1}^i(\mathbf{x}) = \frac{\prod_{j\in\mathcal{N}^i} \left[s_\ell^j(\mathbf{x})\right]^{\omega^{i,j}}}{\int \prod_{j\in\mathcal{N}^i} \left[s_\ell^j(\mathbf{x})\right]^{\omega^{i,j}} d\mathbf{x}} \tag{5}$$

$$p_{\ell+1}^i(n) = \frac{\prod_{j\in\mathcal{N}^i} \left[p_\ell^j(n)\right]^{\omega^{i,j}} \left\{\int \prod_{j\in\mathcal{N}^i} \left[s_\ell^j(\mathbf{x})\right]^{\omega^{i,j}} d\mathbf{x}\right\}^n}{\sum_{m=0}^{\infty} \prod_{j\in\mathcal{N}^i} \left[p_\ell^j(m)\right]^{\omega^{i,j}} \left\{\int \prod_{j\in\mathcal{N}^i} \left[s_\ell^j(\mathbf{x})\right]^{\omega^{i,j}} d\mathbf{x}\right\}^m} \tag{6}$$

where the consensus weights must satisfy

$$\omega^{i,j} \geq 0 \quad \forall i,j \in \mathcal{N}; \qquad \sum_{j\in\mathcal{N}^i} \omega^{i,j} = 1 \quad \forall i \in \mathcal{N}.$$

and the consensus iterations are inizialized by $s_0^i(\cdot) = s^i(\cdot)$ and $p_0^i(\cdot) = p^i(\cdot)$. Let $\mathbf{\Omega}$ denote the $N \times N$ consensus matrix whose generic (i,j) element coincides with the consensus weight $\omega^{i,j}$ if $j \in \mathcal{N}^i$, or is taken as 0 otherwise. In [1] it is shown that if the consensus weights are chosen so that the matrix $\mathbf{\Omega}$ is doubly stochastic and if the network (graph) $\mathcal{G}$ is strongly connected, i.e. for any pair of nodes i and j there is a directed path from i to j, then the regional average (p_ℓ^i, s_ℓ^i), in each node i, tends to the collective average $(\overline{p}, \overline{s})$ as $\ell \to \infty$. Notice that the above consensus step is nothing but a weighted average of CPHDs over a restricted subset of neighboring nodes and is, therefore, scalable with respect to the network size.

4. CONSENSUS MULTITARGET TRACKER

This section presents the proposed CGM-CPHD filter algorithm [1]. The sequence of operations carried out at each sampling interval t in each node $i \in \mathcal{N}$ of the network is reported in Table 1. All nodes $i \in \mathcal{N}$ operate in parallel at each sampling interval t in the same way, each starting from its own previous estimates of the cardinality distribution and location function in GM form, i.e.

$$\left\{p_{t-1|t-1}^i(n)\right\}_{n=0}^{n_{max}}, \quad \left\{\left(\alpha_j^i, \hat{\mathbf{x}}_j^i, \mathbf{P}_j^i\right)_{t-1|t-1}\right\}_{j=1}^{\left(N_G^i\right)_{t-1|t-1}}$$

and producing, at the end of the various steps listed in Table 1, its new estimates of the CPHD as well as the target state estimates, i.e.

$$\left\{p_{t|t}^i(n)\right\}_{n=0}^{n_{max}}, \quad \left\{\left(\alpha_j^i, \hat{\mathbf{x}}_j^i, \mathbf{P}_j^i\right)_{t|t}\right\}_{j=1}^{\left(N_G^i\right)_{t|t}}, \quad \left\{\hat{\mathbf{x}}_{t|t}^{i,j}\right\}_{j=1}^{\hat{n}_{t|t}^i}$$

A brief description of the various steps of the CGM-CPHD algorithm follows below.

1. First, each node i performs a local GM-CPHD filter update exploiting the multitarget dynamics and the local measurement set. The details of the GM-CPHD update (prediction and correction) can be found in [4]. A merging step [3, section III.C, table II] is introduced after the local update and before the consensus phase in order to reduce the number of Gaussian components and, hence, alleviate both the communication and the computation burden.

2. Then, consensus takes place in each node i involving the subnetwork $\mathcal{N}^i$. Each node exchanges information (i.e., cardinality distribution and GM representation of the location function) with the neighbors and carries out the GM-GCI fusion in (5)-(6) over $\mathcal{N}^i$. This procedure is repeatedly applied for an appropriately chosen number $L \geq 1$ of consensus steps.

3. After the consensus, the resulting GM is further simplified by means of a pruning step [3, section III.C, table II]. Finally, an estimate of the target set is obtained from the cardinality distribution and the pruned location GM via an estimate extraction step [3, section III.C, table III].

A detailed description of the overall algorithm can be found in [1].

Table 1: Consensus GM-CPHD pseudo-code

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procedure CGM-CPHD(NODE i, TIME t)
LOCAL GM-CPHD PREDICTION
LOCAL GM-CPHD CORRECTION
MERGING

for $\ell = 1, \ldots, L$ **do**
INFORMATION EXCHANGE
GM-GCI FUSION OVER $\mathcal{N}^i$
MERGING
end for

PRUNING
ESTIMATE EXTRACTION
end procedure

Recently, it has been shown [8] that multisensor PHD is asymptotically optimal increasing the number of sensors. This theoretical result cal legitimate the development of efficient algorithms (like, e.g., CGM-CPHD) which implement the multisensor fusion using the PHD.

5. RANGE-DOPPLER CASE STUDY

In this section, the CGM-CPHD algorithm is applied on a realistic scenario for distributed multitarget tracking by exploiting range and/or Doppler measurements. A 2-dimensional (planar) multitarget tracking scenario is considered over a surveillance area of $50 \times 50[km^2]$, wherein 6 targets are present at different times and a network of 4 Range-Doppler sensors is deployed. A pictorial view of the aforementioned scenario is depicted in Fig. 1.

The target state is denoted by $\mathbf{x} = [x,\ \dot{x},\ y,\ \dot{y}]^T$ where (x, y) and $(\dot{x}, \dot{y})$ represent the target Cartesian position and, respectively, velocity components. The motion of targets is modeled by the filters according to the discrete nearly-constant velocity model [9] with process noise standard deviation $\sigma_w = 2[m/s^2]$ and sampling interval $T_s = 5[s]$.

As it can be seen from Fig. 1, the sensor network considered in the simulation consists of 4 *Range-Doppler* sensors characterized by the following measurement functions:

$$\mathbf{h}^i(\mathbf{x}) = \begin{cases} \sqrt{(x-x^i)^2 + (y-y^i)^2}, & \text{Range} \\ -\dfrac{2}{\lambda}\dfrac{\dot{x}\,(x-x^i) + \dot{y}\,(y-y^i)}{\sqrt{(x-x^i)^2+(y-y^i)^2}}, & \text{Doppler} \end{cases} \quad (7)$$

where (x^i, y^i) represents the known position of sensor i; Doppler measurements are characterized by carrier frequency $f_T = 0.9[GHz]$, i.e. wavelength $\lambda = 0.33[m]$, and standard deviation of measurement noise equal to $\sigma_D = 0.5[Hz]$; the standard deviation of range measurement noise is $\sigma_R = 500[m]$. Please notice the inaccuracy of range measurements (cfr. σ_R). Because of the non linearity of the aforementioned sensors, the *Unscented Kalman Filter* (UKF) [10] is exploited in each sensor in order to update means and covariances of the Gaussian components.

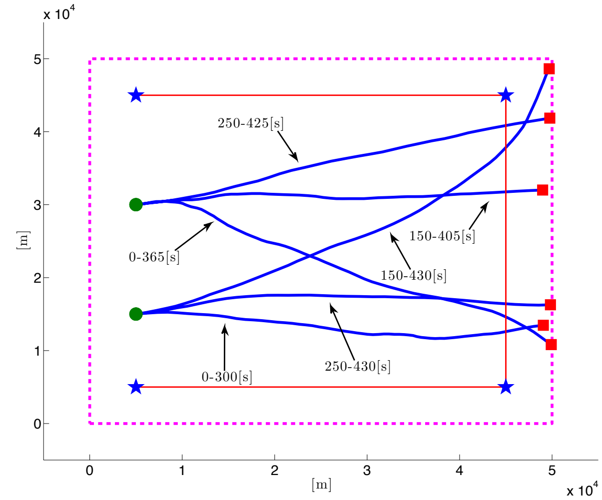

Fig. 1: Pictorial view of the 4 Range-Doppler sensor network and of the 6 target trajectories considered in the simulations. Sensors are denoted with a blue $\star$ while the start/end point for each trajectory is denoted, respectively, by $\bullet / \blacksquare$.

Clutter is generated as a Poisson Process with parameter $\lambda_c = 1$ and uniform spatial distribution over, respectively, the surveillance area and the frequency interval $[-1000, 1000]\,[Hz]$; the probability of target detection is $P_d = 0.99$.

Target birth is modeled and assumed in two possible different locations, described by the following intensity function

$$\begin{aligned} & d_b(\mathbf{x}) = \alpha_1\, \mathcal{N}(x; \hat{\mathbf{x}}_1, \mathbf{P}_1) + \alpha_2\, \mathcal{N}(x; \hat{\mathbf{x}}_2, \mathbf{P}_2) \\ & \alpha_1 = \alpha_2 = 0.15 \\ & \hat{\mathbf{x}}_1 = [5000,\ 0,\ 15000,\ 0]^T \ \ \hat{\mathbf{x}}_2 = [5000,\ 0,\ 30000,\ 0]^T \\ & \mathbf{P}_1 = \mathbf{P}_2 = \mathrm{diag}\left(500^2,\ 100^2,\ 500^2,\ 100^2\right) \end{aligned}$$

Three different situations have been considered, i.e. Doppler-only, Range-only and Range-Doppler tracking. Unfortunately it has been found that, in the Doppler-only case, the CGM-CPHD filter is unable to track targets; hence performance has been compared for the other two, Range-only and Range-Doppler, cases.

Multitarget tracking performance is evaluated in terms of the OSPA (*Optimal SubPattern Analysis*) metric [11]. The reported metric is averaged over $N_{mc} = 200$ Monte Carlo trials for the same target trajectories but different, independently generated, clutter and measurement noise realizations. The duration of each simulation trial is fixed to $500[s]$ (100 samples).

The parameters of the CGM-CPHD filter (see [1] for their definition) have been chosen as follows: the survival probability is $P_s = 0.99$; the maximum number of Gaussian components is $N_{max} = 25$; the merging and truncation thresholds (see [1]) are $\gamma_m = 16$ and $\gamma_t = 10^{-4}$; Metropolis weights [7] have been adopted for consensus.

Fig. 2 reports the OSPA metric (with Euclidean distance, $p = 2$, and cutoff parameter $c = 600$), respectively, for Range-only (red dashed line) and Range-Doppler (green solid line) scenarios. As it can be seen, the performance obtained with Range-Doppler measurements is significantly better then with Range-only measurements. The results of Figs. 2 and 3 also show that, by just applying a single consensus step, performance of the distributed algorithm exploiting Range-Doppler measurements is satisfactory for both estimation and cardinality errors.

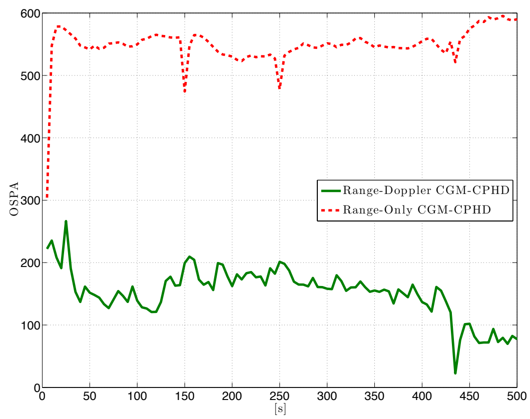

Fig. 2: Performance comparison, using OSPA, between *Range-only* and *Range-Doppler* CGM-CPHD with $L = 1$ consensus steps.

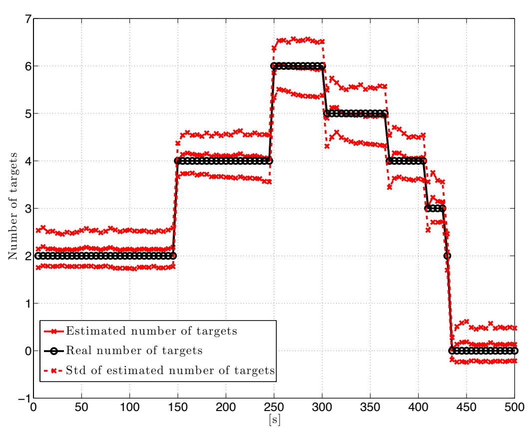

Fig. 3: Cardinality performance for *Range-Doppler* CGM-CPHD with $L = 1$ consensus step.

6. CONCLUSIONS

It has been demonstrated that it is possible to realize an effective distributed surveillance system by connecting sensors that provide Doppler-shift measurements only if some, possibly inaccurate, range measurements are also available. Distributed Doppler-only multitarget tracking, on the other hand, needs to be further investigated in that the currently employed local filtering and fusion algorithms still provide an unsatisfactory behavior.

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