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Distributed joint sensor registration and target tracking via sensor network

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ABSTRACT

This paper deals with distributed registration of a sensor network for target tracking in the presence of false and/or missed measurements. Each sensor acquires measurements of the target position in local coordinates, having no knowledge about the relative positions (referred to as drift parameters) of its neighboring nodes. A distributed Bernoulli filter is run over the network to compute in each node a local posterior target density. Then a suitable cost function, expressing the discrepancy between the local posteriors in terms of averaged Kullback–Leibler divergence, is minimized with respect to the drift parameters for sensor registration purposes. In this way, a computationally feasible optimization approach for joint sensor registration and target tracking is devised. Finally, the effectiveness of the proposed approach is demonstrated through simulation experiments on both tree networks and networks with cycles, as well as with both linear and nonlinear sensors.

1. Introduction

Recently, *distributed detection and tracking* (DDT) of a target by means of a sensor network consisting of low cost and low energy consumption sensors has attracted a great deal of attention due to the rapid advances of wireless sensor technology. The employment of such sensor networks can clearly enhance performance while decreasing cost of surveillance systems. The goal of target DDT is to achieve scalability and comparable performance with respect to centralised architectures. Based on random finite set (RFS) theory [1,2], generalized covariance intersection (GCI) [3] and consensus [4–7], several DDT approaches have been proposed over the past few years [8–12], most of them relying on the assumption that all sensor nodes in the network have been correctly registered/aligned in a common global coordinate system.

In many practical scenarios, however, the problem of sensor registration has to be solved along with target tracking, due to the fact that, in certain circumstances, it is hard to get accurate knowledge about the positions of the deployed sensor nodes. Most of the existing work on registration relied on two approaches. In the first approach, called *cooperative localization*, each sensor is provided with direct measurements relative to positions of its neighbors [13–22]. Conversely, the second approach is based on exploiting some reference nodes of known positions (also called anchors) in the global coordinate system [23–27]. The locations of anchors are assumed known a priori or can be obtained by using global localization technology such as, e.g., GPS (Global Positioning System). Undoubtedly both approaches have their limitations. The former requires additional sensing devices for measuring the positions of the neighboring nodes, and it is hard to obtain the inter-node measurements in some specific scenarios, e.g. confined environments with multipath. The latter can only be used in specific scenarios where either prior knowledge of the surveillance area is available or signals from some global localization system can be received. Conversely, in some specific applications involving, e.g., underwater or indoor environments, wherein the GPS signal cannot be received, this approach is not viable. Hence, both approaches cannot provide satisfactory flexibility for applications. In this paper, the interest is for a technique that neither needs sensing the positions of neighbors nor the presence of reference nodes.

In this respect, several interesting techniques have been recently introduced [28–30]. In particular, Kantas et al. [28] exploit online distributed maximum likelihood (ML) and expectation maximization (EM) methods. The nodes iteratively exchange the local likelihoods based on the message passing (belief propagation) technique. This approach, however, suffers from three major drawbacks. First, each node must store the data of all its neighbors and thus needs a lot of extra memory space. Secondly, at each sampling interval several iterations must be carried out in order to exchange the data through the network. The third and most important drawback is that the employed message passing method is well suited for networks with tree topology but suffers from the problem of double counting of information in networks with cycles, and also is not robust to time-variations of the network topology. The work in [29] adopted the same strategy for sensor

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Acronyms and symbols

DTT	Distributed Detection and Tracking
RFS	Random Finite Set
GCI	Generalized Covariance Intersection
GPS	Global Positioning System
ML	Maximum Likelihood
EM	Expectation Maximization
FISST	FInite Set STatistics
PDF	Probability Density Function
GM	Gaussian Mixture
wKLA	weighted Kullback–Leibler Average
KLD	Kullback–Leibler Divergence
CBF	Consensus Bernoulli Filter
HMM	Hidden Markov Model
TC	Total Cost
IRF	Instantaneous Reward Function
$\mathcal{D}$	directed graph
$\mathcal{N}$	set of sensor nodes
$\mathcal{A}$	set of arcs (connections)
$\mathcal{N}^i$	set of in-neighbors of node i
$\theta^{i,j}$	drift parameter of sensor j with respect to i
Θ	vector of all drift parameters
Θ^i	vector of all drift parameters of node i
x^i	single-target state at node i
p_s	probability of survival of an existing target
p_b	probability of birth of a new target
Q_t	process disturbance covariance
$g_t(\cdot)$	single-target transition function
$p_d^i(\cdot)$	probability of target detection at node i
$h_t^i(\cdot)$	measurement function at node i
R_t^i	measurement noise covariance of node i
$\mathcal{Z}_t^i$	measurement set of node i
C_t^i	clutter set of node i
$\phi_{t\|t-1}(\cdot\|\cdot)$	transition density of target RFS
$\zeta_t^i(\cdot\|\cdot)$	target RFS likelihood function of node i
$f_t^i(\cdot)$	target RFS density
q_t^i	target existence probability
$p_t^i(\cdot)$	target state PDF
$\omega^{i,j}$	consensus weight of neighbor j at node i
L	number of consensus steps
$\mathcal{J}_{t,\ell}^i(\Theta^i)$	cost for sensor registration at node i
$\mathcal{W}_{t,\ell}^i(\Theta^i)$	IRF of node i

registration as in [28], while employing consensus instead of belief propagation for message passing. This would no longer suffer from the above mentioned third drawback of [28]. However, it is hard to exploit the approaches in [28,29] in highly cluttered scenarios wherein nodes need to exchange a lot of false measurements thus involving a great communication load.

Conversely, Uney et al. [30] followed a Bayesian approach in order to compute in each node the posterior distribution of the drift parameters. Specifically, a Monte Carlo method is adopted to represent such a distribution. The disadvantage of [30] is, therefore, that it needs a large amount of particles in order to satisfactorily approximate the drift parameters' distribution, thus implying a heavy computational load which may be unsuitable for sensor nodes with limited computing capabilities and battery energy. Furthermore, Uney et al. [30] also employed the message passing strategy for distributed computation, which also suffered from the same problems of [28] with networks that change in time and/or contain loops.

Nevertheless, to the best of authors' knowledge, all the above mentioned papers except [30] considered only the ideal case wherein the target is assumed to always exist throughout the whole observation period, sensor nodes detect the target with unit probability, and the sensing process is not affected by false alarms (clutter). In this paper, we solve the sensor registration problem in the context of DDT of a target by means of a sensor network. The target is modeled as a Bernoulli RFS [31]. The *FInite Set STatistics* (FISST) density of a Bernoulli RFS consists of an existence probability and of a state PDF, where the former can be used to ascertain target existence, while the latter is used for extracting target state estimate and covariance. By employing a proper likelihood model that considers missed detections and false measurements (like, e.g., (49) of [31]), the Bernoulli filter is able to recursively propagate the target existence probability and state PDF of the Bernoulli RFS. In this paper, the target state PDF of the Bernoulli RFS is approximated by a *Gaussian mixture* (GM). At each sensor node, after carrying out Bernoulli filtering with the local measurement set and exchanging posterior local Bernoulli densities with neighbors, the weighted average of Kullback–Leibler divergences from the local posterior Bernoulli densities to their *weighted Kullback–Leibler Average* (wKLA) [32] is employed as cost function in order to measure the discrepancy between estimated and true drift parameters. Then, sensor registration is carried out by minimizing with respect to the drift parameters such a cost function. In other words, the sensor registration step of the proposed algorithm is carried out by exploiting the discrepancies of the kinematic information related to the same target in different local coordinates. In this respect, sensor registration is successfully accomplished whenever there exists a target in the surveillance area, and all the nodes in the network have full target observability, which are also the basic requirements for the method in [30]. The proposed sensor registration algorithm can be combined with the *Consensus Bernoulli Filter* (CBF) [9] in order to jointly align sensors, detect the target and track it. The remarkable feature of the proposed approach is that it introduces no additional data exchanges, only little extra additional computational load and memory requirements comparable to the original CBF. Further, the proposed algorithm is insensitive to the type of sensor network, a feature that is inherited from the properties of consensus.

To summarize, the main contribution of this paper is to propose an algorithm that can:

- allow distributed registration of a sensor network for joint detection and tracking of a target in the presence of clutter and misdetections;
- perform sensor registration with neither prior information nor direct measurements on the position of sensor nodes;
- be applied to sensor networks with arbitrary topology.

The rest of the paper is organized as follows. Section 2 illustrates the considered scenario and reviews the background needed for the proposed sensor registration algorithm. In Section 3, the algorithm is first presented, and then a tractable optimization strategy is introduced in order to estimate the drift parameters. A possible combination of the proposed sensor registration algorithm and the CBF is also illustrated in Section 3. Section 4 provides simulation examples in order to demonstrate the effectiveness of the proposed approach. Section 5 ends the paper with concluding remarks as well as perspectives for future work.

2. Problem formulation and background

2.1. Problem formulation

Let us consider a network wherein each node can:

- get measurements of kinematic variables (e.g. angles, distances, Doppler shifts, etc.) relative to a single target moving in the