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A distributed particle filter for nonlinear tracking in wireless sensor networks

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ABSTRACT

The use of distributed particle filters for tracking in sensor networks has become popular in recent years. The distributed particle filters proposed in the literature up to now are only approximations of the centralized particle filter or, if they are a proper distributed version of the particle filter, their implementation in a wireless sensor network demands a prohibitive communication capability. In this work, we propose a mathematically sound distributed particle filter for tracking in a real-world indoor wireless sensor network composed of low-power nodes. We provide formal and general descriptions of our methodology and then present the results of both real-world experiments and/or computer simulations that use models fitted with real data. With the same number of particles as a centralized filter, the distributed algorithm is over four times faster, yet our simulations show that, even assuming the same processing speed, the accuracy of the centralized and distributed algorithms is practically identical. The main limitation of the proposed scheme is the need to make all the sensor observations available to every processing node. Therefore, it is better suited to broadcast networks or multihop networks where the volume of generated data is kept low, e.g., by an adequate local pre-processing of the observations.

1. Introduction

Due to the falling size and costs of suitable hardware, the deployment of wireless sensor networks (WSNs) is becoming an increasingly attractive option for a growing number of tracking applications. Examples include security and surveillance [5], environmental monitoring (tracking of weather patterns and pollutants) [32], monitoring in domestic situations (such as in care for the elderly) [22], and biology (tracking of populations or individual animals) [27].

Distributed applications of tracking are particularly interesting in situations where high powered centralized hardware cannot be used. For example, in deployments where computational infrastructure and power are not available or where there is no time or trivial way of connecting to it. In these scenarios, and possibly many others, the signal processing tasks associated to target tracking need to be shared by the multiple nodes of the WSN. Note that many items in the literature often refer to WSNs as being "distributed", even when processing is centralized, because they are merely referring to the physically distributed nature of WSNs. See, for example [9,18]. In this paper we refer to "distributed" specifically with regard to processing, meaning that the computational tasks are divided among a set of low-power devices in the WSN.

1.1. Distributed particle filters

Stochastic filtering methods [3] are obvious candidates for tracking applications and so they have been researched by many authors in the context of WSNs [29,14,11]. Such work includes, e.g., networks of interacting Kalman filters [30], although in this case the emphasis is on the minimization of the communications among nodes, rather than the sharing of the computational load.

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Particle filtering for target tracking in WSNs has already attracted some attention (see, for example, [5,1,2]), including a body of work in distributed methods [10,21,7]. Its relation with agent networks has also been explored in [20]. In [7], a fully decentralized particle filtering algorithm for cooperative blind equalization is introduced. The technique is proper, in the sense that it does not make any approximations in the computation of the importance weights of the particles. However, the scheme is applicable only when the state signal is discrete, and would be infeasible in terms of computation and communication among nodes (the authors provide a simulation only) in WSNs such as we consider. In [10], the communication load is reduced using quantization and parametric approximations of densities. A similar parametric approach is applied in [21] to further simplify communications. Even though these parametric approximations are practical for their implementation on a WSN they compromise the estimation accuracy and, to our view, take away the main advantage of the particle filter (PF): its generality and capability to perform numerical inference, with full theoretical guarantees, on arbitrary state-space dynamical systems.

Recently, a class of interacting PFs has been proposed for multi-target tracking [13]. This class of algorithms relies on splitting the state-space into lower dimensional subspaces in order to become computationally tractable, but does not guarantee that the particles are assigned proper weights.

The majority of existing contributions related to particle filtering and WSNs, only offer a theoretical perspective and/or computer simulation studies, owing in part to the challenges of real-world deployment and testing on low-powered hardware. Deployments of physical sensor networks have so far been almost exclusively centralized implementations (from the computational point of view held in this paper). For instance, in [2], 25 acoustic sensors are used with a centralized PF to track a remote-controlled car; the authors of [1] use the received signal strength (RSS) measurements to track an additional moving target node. There are a few exceptions of actually distributed PFs, but they are approximations to the centralized PF whose convergence cannot be guaranteed [26].

The use of the non-parametric loopy belief propagation (NPBP) algorithm has also been suggested for localization and tracking [33] in the same context as particle filtering. This algorithm is an extension of the belief propagation algorithm to continuous variables and it uses a graph to represent the decomposition of the joint posterior. Its main advantage resides in exploiting the rich underlying structure that often arises in image processing or in sensor self-localization. Unfortunately, the NPBP scheme poses difficulties for a real-time implementation and there is, to the best of our knowledge, no rigorous proof of convergence for this algorithm.

1.2. Distributed resampling with non-proportional allocation (DRNA)

Particle filtering algorithms involve three basic steps: generation of samples, computation of weights and resampling [12]. While it is straightforward to parallelize the first two steps, resampling requires the joint processing of all the samples in the filter and so becomes a computational bottleneck. The distributed resampling with non-proportional allocation (DRNA) algorithm [6] (see also [28] for some further analysis) addresses the parallelization of the resampling step to remove this bottleneck.

The DRNA algorithm was devised to speed up the computations in particle filtering. The basic assumption in [6] is the availability of a set of processors interconnected by a high-speed network, in the manner of state-of-the-art graphical processing unit (GPU) based systems [25]. Such network is intended to guarantee that all processors in the system have access to the full set of observed data.

In a typical WSN, the communications among nodes are subject to various constraints (i.e., transmission capacity, power consumption or error rates), hence the hardware setup is fundamentally different from the one assumed in [6] or [28]. The issue of whether the DRNA scheme can be efficiently exploited in a typical WSN deployment has not been addressed, to the best of our knowledge, neither experimentally nor even by realistic simulation studies.

1.3. Contribution and organization

In this work we tackle the problem of implementing the DRNA algorithm in a practical WSN. We first revisit the standard PF and its combination with the DRNA algorithm, providing a formal description of the methodology. This includes simple analysis showing that (a) the importance weights are proper and (b) the resampling scheme is unbiased. While intuitively expected, these two simple results had not been given explicitly in [6,28].

In the second part of the paper, we address the practical implementation of a distributed PF for target tracking, based on the DRNA scheme, that runs in real time over a WSN. We have developed a software and hardware testbed implementing the required algorithmic and communication modules in physical nodes, equipped with light-intensity sensors but with limited processing and communication capabilities. We assess the tracking performance of the resulting system in terms of the tracking error obtained with both synthetic and real data. Finally, we study the constraints in the real-time operation and the communication capabilities (compared to a centralized PF) by way of experiments with our testbed implementation.

The main limitation of the proposed scheme is that every node performing a subset of the computations of the PF should have access to all the observations (i.e., all the measurements collected by the WSN at the current time step) in order to guarantee that the particle weights are proper and, therefore, the resulting estimators consistent. The DRNA-based PF, therefore, is better suited to broadcast networks or multihop WSNs where the volume of data generated per time step is limited. The algorithm can still be applied with different sets of observations available at each node, but in that case the particle weights are only proper locally (at each node) and not globally (over the whole network).

The rest of the paper is organized as follows. In Section 2 we introduce the problem of target tracking in the context of