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Improved distributed particle filters for tracking in a wireless sensor network

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ABSTRACT

A novel distributed particle filter algorithm is presented, called drift homotopy likelihood bridging particle filter (DHLB-PF). The DHLB-PF is designed to surmount the degeneracy problem by employing a multilevel Markov chain Monte Carlo (MCMC) procedure after the resampling step of particle filtering. DHLB-PF considers a sequence of pertinent stationary distributions which facilitates the MCMC step as well as explores the state space with a higher degree of freedom. The proposed algorithm is tested in a multi-target tracking problem using a wireless sensor network where no fusion center is required for data processing. The observations are gathered only from the informative sensors, which are sensing useful observations of the nearby moving targets. The detection of those informative sensors, which are typically a small portion of the sensor network, is taking place by using a sparsity-aware matrix decomposition technique. Simulation results showcase that the DHLB-PF outperforms current popular tracking algorithms.

1. Introduction

The reconstruction of unknown quantities from noisy observations is a common subject in several engineering and scientific problems, such as target tracking, Mahler (2007), and weather forecasting, Monache et al. (2011). Statistically this is a nonlinear filtering problem which consists of two stochastic processes, the signal process we want to estimate and the observation process which yields information about the unobserved signal, e.g. see Xiong (2008). In general, the signal is modeled by a Markov process, which is described by a certain stochastic equation. The observation process is typically a function of the signal process perturbed by a random noise. A popular method for a computational implementation of filtering is particle filtering.

Particle filtering approximates the posterior distribution of interest by a set of appropriately weighted samples, called particles. Although a widely used method, it may degenerate if several time steps and multiple signals are involved, or it may require a large number of particles to approximate the true underlying posterior distribution. The reason is that typically only a few samples have dominant weights and the rest of weights are close to zero. It has actually been shown in Snyder et al. (2008) that only one sample carries the approximation and has a nonzero weight for high dimensional problems. The problem of degeneracy carries over in other complex problems, e.g. due to large number of signals under consideration for a long time horizon in the multi-target tracking problem using a wireless sensor network (WSN). To this

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end, we propose a novel particle filter, what we call, a drift homotopy likelihood bridging particle filter algorithm (DHLB-PF). We engage the idea of appending an extra Markov chain Monte Carlo (MCMC) step after the resampling step which aims to move the particles to statistically significant regions while at the same time the state space is explored with high degrees of freedom. The idea of the DHLB-PF resembles the principles of annealing suitably applied to the nonlinear filtering problem by aiding the appended MCMC step to explore the state space with great flexibility. Moreover, not only the current particles are resampled based on the newly arrived observation (as in the standard resampling technique) at the modified resampling step, but also the associated previous ones are stored. The idea is that highly weighted "children" particles have been produced by highly weighted "parent" particles in similar spirit à la (Weare, 2009).

Additionally, the nature of the posterior distribution needs to be preserved. Consequently, we design a sequence of intermediate stationary distributions to facilitate the appended MCMC process by taking advantage of the fact that the posterior distribution is proportional to the product of a pertinent transition density, characterized by the original signal process, and a likelihood density based on the noisy data. To that end, the drift homotopy likelihood bridging (DHLB) technique considers a two-fold simultaneous approach. First, the *drift homotopy* considers a sequence of stochastic differential equations (SDEs) with modified drifts that interpolate between the original and modified drifts. At the same time, the *likelihood bridging* considers a sequence of modified likelihood densities starting from the uniform likelihood density. The interpolation of dynamics and likelihood bridging engage multiple levels with the final level corresponding to the original posterior distribution. All levels are auxiliary and aim to facilitate the MCMC sampling with a good initial condition, while the state space is explored with a great flexibility due to the intermediate likelihood levels. Specifically, using an appropriate MCMC scheme, one samples particles at current level with an initial condition the particles at previous level. The DHLB technique allows us to gradually move particles into statistically significant regions while at the same time respecting the nature of the posterior distribution.

Next, we employ the DHLB-PF in a sparse environment and examine its performance in tracking multiple objects whose signals are collected by a WSN. The deployment of sensor networks allows the collection and distributed processing of information in challenging environments whose structure is unknown and is dynamically varying in time (Caudle and Wegman, 2009). In such environments, the network itself, as well as humans, is prone to spatiotemporally unpredictable threats that may be generated due to malicious attacks, functional failures and even human errors. Thus, effective and rapid detection and tracking of such targets is essential.

Multi-object identification and trajectory estimation require first a robust association of sensors information with targets across space and time. There is a plethora of ways to proceed with the multi-object tracking, using Kalman filter and its derivatives, as well as particle filters or random sets. For example see the partial list of Baum and Hanebeck (2013, 2012), Kang et al. (2014), Maroulas et al. (2015), Liu and Chen (1998), Vo et al. (2005), Maroulas and Nebenfuhr (2015) and references therein. Particle filtering method is one of the most popular methods for tracking given its flexibility to avoid any distributional assumptions in contrast to Kalman filter or random set approaches, e.g. see Mahler (2007) and Mahler and Maroulas (2013). On the other hand, any of these methods need to engage directly with sparse measurements from a wireless sensor network. Targets present in the sensing field affect only a small portion of the deployed wireless sensor networks (WSNs). Thus, given the limited resources, it is pertinent to identify the sensors that acquire information-bearing observations about the targets and use only those which provide such information. Many existing tracking techniques require all sensors to be active, e.g. see Ahmed et al. (2010), Hlinka et al. (2013), Olfati-Saber (2005), Ozdemir et al. (2009), Zhu et al. (2009), Jeske et al. (2009) and Shin et al. (2007), or at least multiple local fusion centers are required for data processing as in Coates (2004) which may be resource-consuming given the locality of the objects affecting only a small number of sensors.

To this end, a distributed algorithmic framework is also developed here that associates targets with the sensors that acquire informative measurements about these targets, and subsequently performs tracking using only these informative sensors. Specifically, sensors which are positioned close to the same target, acquire data measurements that tend to be correlated. Such correlations induce a sparse structure in the sensor data covariance matrix, which is time-varying since the objects are moving within the sensing region. Consequently, a pertinent framework is derived to analyze the sensor data covariance into sparse factors whose support will indicate subsets of sensors sensing the same target. Different from Guan et al. (2012), Hoyer (2004), Lee and Seung (2001), Lin (2007), Ulfarsson and Solo (2008) and Zou et al. (2006), the matrix factorization scheme developed here does not impose structural requirements to the unknown factors such as orthogonality and/or positivity of the factor entries. Once the information of pertinent sensors has been acquired based on the support of the sparse factors which are obtained via sparsity-aware data covariance matrix decomposition, the drift homotopy likelihood bridging particle filtering engages in order to estimate the objects' trajectories using the generalized Hybrid Monte Carlo (gHMC) method, which is an advanced MCMC scheme. The exploitation of the covariance sparsity which depends on the time-varying statistical behavior of the data and the interplay of the sparse factorization framework with the DHLB-PF approach employing the gHMC is novel and leads to a new trajectory estimation algorithm.

The paper is organized as follows. Section 2 describes the basic particle filtering method with resampling. Section 3 provides a detailed description of the drift homotopy likelihood bridging method, as well as a motivating example related to a rugged double well potential model which arises in problems of protein folding and spin glasses. Moreover, benchmarking with other particle filter methods which aid to reduce the particle filter's degeneracy problem is shown. Section 4 describes the problem formulation related to tracking within a wireless sensor network. Further, an analysis of the time dependent covariance matrix into sparse factors is offered so that sensor data are associated with targets. Numerical results and a comparison with other methods are exposed and a conclusion is presented in Section 5.