Signal Processing 120 (2016) 627–643

Contents lists available at ScienceDirect

Signal Processing

journal homepage: www.elsevier.com/locate/sigpro

Decentralized sparsity-based multi-source association and state tracking ☆

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ARTICLE INFO

Article history:
Received 11 May 2015
Received in revised form
3 September 2015
Accepted 5 October 2015
Available online 23 October 2015

Keywords:
Sparsity
Multi-source tracking
Distributed processing
Sensor-to-source association

ABSTRACT

The problem of tracking multiple sources using observations acquired at spatially scattered sensors is considered here. Two different sensing architectures are studied: (i) a fusion-center based topology where sensors have a limited power budget; and (ii) an ad hoc architecture where sensors collaborate with neighboring nodes enabling in-network processing. A novel source-to-sensor association scheme and tracking is introduced by enhancing the standard Kalman filtering minimization formulation with norm-one regularization terms. In the fusion-based topology a pertinent transmission power constraint is introduced, while coordinate descent techniques are employed to recover the unknown sparse observation matrix, select pertinent sensors and subsequently track the source states. In the ad hoc topology, the centralized minimization problem is written in a separable way and the alternating direction method of multipliers is utilized to construct an in-network algorithmic tracking and association framework. Numerical tests demonstrate that the resulting schemes are capable to associate sources with sensors, and track the unknown sources while adhering to any imposed power constraints.

1. Introduction

The task of tracking simultaneously many sources using sensor measurements at spatially scattered locations is extremely useful in a number of applications varying from surveillance to environmental monitoring [2]. The majority of existing tracking approaches, such as the network schemes in [1,11,10,23,26,43,27], extend standard techniques such as Kalman filtering or particle filtering [3,12]. The aforementioned approaches are developed under the assumption that the sensing model parameters are available. Such an assumption enables sensors to identify which sources they sense, which can further simplify the tracking process. However, in many settings it is not known which sensors observe each of the underlying field sources, while the signal attenuation from a source to a sensor is unavailable giving rise to an observation model with unknown parameters. In such settings source-to-sensor association is essential.

Alternative Kalman filtering schemes have been designed for settings where there is uncertainly in the state and observation model parameters which are known with some additive error involved [22,32]. A robust Kalman filter is developed in [40], which relies on the assumption that an uncertainty norm in the state and measurement models can be upper bounded. The latter work is extended in [41] to incorporate uncertainty with an upper bounded norm in the state and measurement noise covariance matrices. Robust Kalman filtering approaches have also been developed in sensor network settings. The work in [20] considers uncertainties in the

☆ Work in this paper is supported by the NSF Grant CCF 1218079, the AFOSR Grant FA9550-15-1-0103, Simons Foundation Award 279870 and UTA.

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http://dx.doi.org/10.1016/j.sigpro.2015.10.013
0165-1684/

measurement model introduced by an unknown sensor-to-fusion center channel. The channel follows a probabilistic on-off model, which is assumed known, and incorporated in the Kalman filter, to decide whether to use or drop measurements. Similarly, the work in [28] considers the design of Kalman filtering techniques in the presence of noise covariance matrix uncertainties with a bounded norm for a fusion-center based multisensor setting.

Different from these approaches, here no a priori information is available about the observation model parameter values, i.e., the sensing matrix entries. Availability of a model is crucial in associating the sources with the sensor measurements. Existing data association schemes [25,13,37,15,24] match observations with sources across time and rely on probabilistic models. Differently, the sensors–sources association scheme proposed here is relying only on the acquired sensor data and no probabilistic models are adopted. A different approach is followed in [35] where multiple fusion centers are present in the sensor network and evaluate the posterior Cramer–Rao lower bound that requires knowledge of the underlying data model. This type of bounds cannot be calculated in our setting. Data association of targets and measurements in the context of radar target tracking resort on probabilistic models to associate radar measurements acquired at different time instances with different targets or clutter [38,39]. In our setting the association of sources and sensors will be performed both in space, due to the presence of scattered sensors, and time without the availability of a sensing model.

In practice, sources present in the monitored field are localized and affect only a small percentage of the sensors present in the sensor network (SN). For instance ground vibrating sources produce signals that undergo an exponential attenuation as they propagate in the ground. Such signals can be sensed in the measurements of sensors located a few meters away from the sources [16]. Interestingly, such a localized structured can be translated to a sensing matrix which has a large number of negligible (or zero) entries, i.e., a sparse matrix. Sparsity is exploited here to recover the unknown sparse sensing matrix in the measurement model, while tracking the different source states. To this end, norm-one regularization techniques, see e.g., [34,44], will be employed to enhance the standard Kalman filter framework. The idea of sparsity has been exploited in the context of tracking [8,36,18], though the difference with respect to the present setting is that sparsity is in the source states and not in the sensing matrix.

Sparsity in the sensing matrix will be exploited here to jointly recover the sensing matrix and obtain tracking estimates for the, *not necessarily sparse*, field source states. The minimization formulation for the Kalman filter/smoother, see e.g., [3], will be enhanced with a pertinent norm-one regularization term. The sparsity-inducing terms will enable associating sources with sensors, and thus identify the sensors that acquire informative observations about the sources and use only those subsequently for tracking. Many existing tracking techniques require all sensors to be active [1,43,26,27] which may be resource-consuming given the locality of the sources and the fact that only a few sensors bear information.

Two different network topologies of complementary nature are considered here. A fusion center (FC) based topology is considered first in which a fusion center is responsible for processing the sensor data and carrying out the association and tracking. Sparsity is combined with the introduction of a power constraint that enables utilization of a small percentage of sensors that are source-informative while a transmission power budget is not exceeded. The resulting novel constrained minimization formulation is tackled here via coordinate descent tools, see e.g., [4]. Power considerations have been incorporated in estimation and tracking [9,17], though without taking into consideration issues such as source-to-sensor association and unknown model parameters.

The requirement for a more scalable and failure-relisient sensing architecture, while compromising computational speed, leads to tackle the novel norm-one regularized Kalman minimization framework in an ad hoc sensing topology. After reformulating the latter minimization problem in a separable form, the alternating direction method of multipliers (ADMM) combined with block coordinate descent, see e.g., [4,5], is utilized to obtain an in-network algorithmic scheme that is capable of associating sensors with sources while tracking the source states.

The paper is organized as follows. The two different sensing topologies along with the problem setting are outlined in Section 2. Building on the standard minimization formulation for the Kalman filter/smoother in [3], a pertinent norm-one regularization mechanism is used to jointly recover the sensing matrix, associate sources with sensors and track the source states. Further, power constraints are introduced to comply with a desired power transmission budget (Section 3). A separable formulation of the sparsity-aware Kalman formulation and applicability of the ADMM toolbox is done in Section 4, resulting an effective in-network algorithm. Different from the preliminary work in [29] here (i) a more refined formulation is provided; (ii) ad hoc topologies are considered and distributed algorithms are derived; and (iii) rigorous theoretical analysis accompanies the algorithmic construction process. A discussion about the communication and computational complexity can be found in Section 5, whereas extensive numerical tests studying the performance of the proposed framework are given in Section 7.

2. Problem statement

Consider a field sensed by a total of p sensors. Each sensor, say j, acquires scalar measurements $x_j(t)$ at time instant $t = 0, 1, 2, \ldots$. Sensor observations contain information about r underlying sources $s_\rho(t)$ which are represented by the scalar random variables $s_\rho(t)$, for $\rho = 1, \ldots, r$. Source signals stacked in the state vector $\mathbf{s}_t := [s_1(t) \ldots s_r(t)]^T$ evolve according to the model:

$$\mathbf{s}_t = \mathbf{F}\mathbf{s}_{t-1} + \mathbf{u}_t, \tag{1}$$