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Distributed fusion estimation in networked systems with uncertain observations and Markovian random delays

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ABSTRACT

This paper addresses the least-squares linear estimation problem in networked systems with uncertain observations and one-step random delays in the measurements. The uncertainties in the observations and the delays are modeled by sequences of Bernoulli random variables with different characteristics for each sensor; the uncertainties are described by independent random variables whereas the delays are modeled by homogeneous Markov chains. The estimators are obtained by a distributed fusion method; specifically, for each sensor, local estimation algorithms are derived by using the information provided by the covariance functions of the processes involved in the observation model, as well as the probability distributions of the variables modeling the uncertainties and delays. The distributed fusion filter and fixed-point smoother are then obtained as the linear combination of the corresponding local linear estimators verifying that the mean squared error is minimum.

1. Introduction

Sensor networks play an important role in the study of complex systems such as engineering systems, military sensing and physical security, and in recent years, the question of estimation in sensor networks has attracted considerable attention in research attention. In order to address the signal estimation problem, information provided by the different sensors is usually combined by means of two different fusion techniques. The first of these, the centralized method, obtains the estimator by jointly processing the measurements of all the sensors at each instant of time. The distributed or decentralized method uses the information provided by the local estimators to obtain the signal estimator. Both methods have been widely utilized although nowadays the distributed method tends to be preferred due to its computational advantages and practical applications. The main interest of this approach lies in how to combine local estimators obtained from the different sensors; in this context, various optimization criteria have been considered, for example, Kim [1] proposed an optimal fusion estimator in the maximal likelihood sense and other authors have obtained the fusion estimator by the well-known weighted fusion algorithm in the linear minimum variance sense (see e.g. [2–4]).

In the transmission of measurement data, ideal assumptions such as unlimited amplitudes or perfect channels are not always possible. In fact, errors commonly occur during the signal transmission, which can lead to different kinds of uncertainties in measurements, for example, measurements containing only noise (uncertain observations), random delays in the arrival of the measurements or packet dropouts. Assuming only one of the

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above uncertainties the signal estimation problem has been studied under different hypotheses on noises and the uncertainty using both the state-space model of the signal (see e.g. [5–8] and references therein) and covariance information (see [9–12] and references therein).

As commented above, the estimation problem in complex systems is now normally addressed by means of sensor networks and, in this context, the use of the distributed method, rather than the centralized method, has attracted much interest due to the above-mentioned advantages. The estimation problem in systems with one of the above uncertainties, uncertain observations, packet dropouts or random delays, is addressed in [14–18] using a distributed fusion algorithm based on scalar and/or matrix weights. In most of these papers, Bernoulli random variables are used to model the uncertainties and the estimation problem is studied under different hypotheses on processes involved in the system. Specifically, assuming that some observations may be only noise, Nahi [13] was the first to obtain a solution to the linear filtering problem assuming the Bernoulli random variables to be independent and also that the additive noises of the signal and the observation are uncorrelated. In [14] a recursive algorithm for the linear filter is derived under the assumption of correlated noises at the same time and adjacent time. Later, Caballero et al. [15] generalized the results of Teng et al. [14], deriving a recursive algorithm for the least-squares linear filter assuming that the uncertainties are described by scalar random variables with arbitrary discrete distribution probability and that the additive noises are autocorrelated and cross-correlated. For systems with packet dropouts, Ma et al. [16] obtained distributed fusion estimators, including predictor, filter and smoother, under the assumption of different packet dropout rates. Liu et al. [17] assumed that the delays are modeled by independent Bernoulli variables, and obtained a distributed fusion filtering algorithm. Recently, García-Ligero et al. [18] generalized the results obtained by Liu et al. [17], assuming that random delays are modeled by homogeneous Markov chains, which is a suitable way to model the dependence on the random delays.

The aforementioned papers focus on estimating the signal from observations affected by only one of the stipulated uncertainties; however in many situations it seems reasonable to consider that measurements will be affected by more than one uncertainty. Recently, the study of systems including more than one uncertainty, simultaneously, has attracted interest; this question has been addressed from various approaches. For example, Sun et al. [19] developed estimation algorithms for systems with one-step random delays and multiple packet dropouts. Moayedi et al. [20] derived an adaptive Kalman filter, defining a unified augmented model to describe the triple uncertainty and a four-state Markov chain to model the whole uncertain system. Using three sequences of Bernoulli variables to describe the three kinds of uncertainty, Ma et al. [21] used an innovation approach to develop optimal linear estimators, including predictor, filter and smoother, in the linear minimum variance sense. Recently, Caballero et al. [22] introduced a new observation model that simultaneously included the three sources of uncertainty, and addressed the least-squares linear estimation problem by means of covariance information.

The present paper considers a multi-sensor environment and addresses the least-squares linear estimation problem in systems affected by two sources of uncertainty, uncertain observations and random delays. These uncertainties are modeled by sequences of Bernoulli random variables with different characteristics in each sensor; the missing measurements are described by independent Bernoulli random variables and the random delays are modeled by different homogeneous Markov chains, which provide a reasonable description of the dependence that usually exists in real communication systems. Assuming no signal equation is available, estimators for each sensor are derived from the information provided by the covariance functions of the processes involved in the observation model, together with the knowledge of the probability distributions of the variables that model the uncertainties and delays. These least-squares linear local estimators, including filter and fixed-point smoother, are obtained using an innovation approach which enables the estimation algorithms to be derived straightforwardly. The distributed fusion filter and the fixed-point smoother are obtained as a linear combination of the corresponding local estimators using the mean squared error as the optimality criterion.

In this paper, as in [18], we assume that the state-space model of the signal is not available. But, unlike [18], where only measurement delays are considered, our aim in the current paper is to obtain a least-squares linear estimation algorithm from uncertain observations, with different uncertainty probabilities in each sensor, transmitted by multiple sensors featuring a one-step delay with different delay rates. The difference between the developments set out in this paper and those in [18] concerns the innovation process and the corresponding covariance and cross-covariance matrices, a factor of fundamental importance, since an innovation approach is used to obtain the least-squares linear local estimators.

We point out that for cases presenting only one uncertainty, missing measurements or random delays, the corresponding estimators can be obtained as a special case of the estimators proposed in this paper.

This paper is organized as follows. In the next section the observation model and the distributed fusion method are described. In Section 3, estimation algorithms are deduced in order to obtain the filter and the fixed-point smoother for each sensor. Then, in Section 4, the distributed fusion filter and the fixed-point smoother, together with the estimation error covariance matrices, are derived. Finally, in Section 5, a simulation example is presented, in which a scalar signal is estimated from observations coming from two sensors affected by two sources of uncertainty, uncertain observations and random delays, with different characteristics for each sensor. The effectiveness of the estimators obtained is determined by means of the filtering and smoothing error variances.

2. Problem statement

2.1. Observation model

Consider an n-dimensional signal, x_k, observed from m sensors that provide scalar measurements, $z_k^i, i = 1, \ldots, m$,