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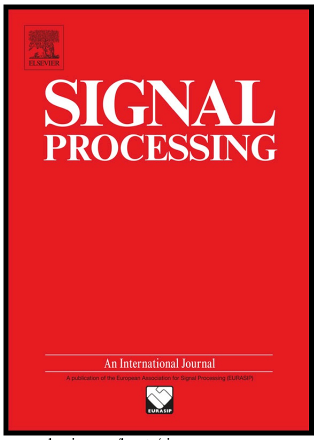

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A switching strategy for adaptive state estimation

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Abstract

This paper develops a switching strategy for adaptive state estimation in systems represented by nonlinear, stochastic, discrete-time state space models (SSMs). The developed strategy is motivated by the fact that there is no single Bayesian estimator that is guaranteed to perform optimally for a given nonlinear system and under all operating conditions. The proposed strategy considers a bank of plausible Bayesian estimators for adaptive state estimation, and then switches between them based on their performance. The performance of a Bayesian estimator is assessed using a performance measure derived from the posterior Cramér-Rao lower bound (PCRLB). It is shown that the switching strategy is stable, and yields estimates that are at least as good as any individual estimator in the bank. The efficacy of the switching strategy is illustrated on a practical simulation example.

Keywords: nonlinear systems; state estimation; posterior Cramér-Rao lower bound; and switching strategy.

1. Introduction

Recent advances in high-speed computing technology have lead to the frequent use of stochastic nonlinear models to represent complex system dynamics. The design and implementation of advanced control or monitoring strategies using such complex models require real-time estimation of the key system states and parameters that are either unmeasured or unknown. In situations, where the parameters are precisely known, the states can be estimated under the Bayesian framework by computing the state posterior density (Tulsyan et al., 2016b). The state posterior density is often computed by solving a state filtering problem (Arulampalam et al., 2002). A closed-form solution to the filtering problem exists for linear state space models (SSMs) under the Gaussian noise settings or when the state space is finite (Arulampalam et al., 2002). Unfortunately, in many engineering systems, the model is often nonlinear and the parameters are not known or time-varying, and therefore need to be estimated before the states can be estimated. In practical settings, adaptive state estimation (simultaneous state and parameter estimation) is often the only realistic solution for it avoids processing of large data set and also allows for adaptation to the time-varying system behavior (He et al., 2011; Kravaris et al., 2013; Ding, 2014).

We consider the problem of online adaptive Bayesian state estimation in general nonlinear stochastic SSMs. In general, this is a difficult problem even for a linear system, as the joint state and parameter posterior density does not lend itself to any closed-form solution (Li et al., 2004). There are several important classes of Bayesian methods for adaptive state estimation, which include - artificial dynamics approach (ADA), practical filtering, Markov chain Monte-Carlo (MCMC) with sequential Monte-Carlo (SMC) methods and SMC^2. A detailed exposition of Bayesian estimators and its approximations can be found in Kantas et al. (2009). Although tractable, the performance of these Bayesian estimators depends on the underlying numerical and statistical approximations used in their design. Unfortunately, there is no single tractable online Bayesian estimator that is guaranteed to perform consistently on a given system or retain a satisfactory performance under all operating conditions. A practitioner is thus left with no clear substitute for the optimal Bayesian estimator.

This paper develops an efficient strategy for adaptive Bayesian state estimation in general nonlinear SSMs. At the outset, it is highlighted that the paper only deals with the class of Bayesian estimators and not with maximum-likelihood estimators. Further, we restrict ourselves only to the class of online Bayesian estimators. The preliminaries of adaptive state estimation are provided next.

2. Preliminaries

In this section, we: (i) define a discrete-time stochastic SSM; (ii) introduce the adaptive state estimation problem; and (iii) highlight our contributions.

Notation: The common notation are first introduced. Here, the notation is broadly classified by topic.

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