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Recursive estimation for Markov jump linear systems with unknown transition probabilities: A compensation approach

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Abstract

This paper considers the minimum mean square error estimation problem for a class of jump Markov linear systems (JMLSs) with unknown transition probabilities (TPs). Compared with other existing estimators, the underlying real but unknown TPs addressed in our method are allowed to be time-variant. The expectation and covariances of residual error in the traditional interacting multiple-model (IMM) algorithm are computed analytically to show that Kalman filter running under true mode can still perform satisfactorily in the presence of wrong TPs. A compensation operator which heuristically modifies the posterior probabilities by adjusting a compensation parameter automatically is then developed. The proposed method is recursive and reduces to IMM method when the compensation parameter goes to value one. Application results for a simulated system are presented to demonstrate the effectiveness.

1. Introduction

As a special class of hybrid systems, jump Markov linear systems (JMLSs) have been used to model a wide variety of dynamical systems with unpredictable system structures, which are

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caused by sudden environment changes, system failures occurred in components or abrupt variation of the operating point. In JMLSs, a Markov process or a Markov chain with a prior transition probabilities matrix (TPM) is employed to index the modes and describe the stochastic characteristics of system behaviors. Over the last three decades, JMLSs have been extensively studied in many different aspects, including controllability, observability, stability and filter design (see [1–6] and references therein), since it provides a useful tool to depict practical systems more realistically. Up to now, many results related to filtering and estimation have been reported for JMLSs, such as multiple-model filtering [7], risk-sensitive filtering [8], particle filtering [9,10], robust filtering [11] and H_∞ filtering [12,13]. Among them, one of the well-known techniques is the interacting multiple-model (IMM) algorithm introduced by Blom and Bar-Shalm in [7]. As it reserves the recursive structure of Kalman filter and makes a good trade off between estimation accuracy and computational load, numerous novel algorithms including particle filter-IMM and variable structure-IMM methods have been proposed [14–16].

Although considerable estimators have been derived for JMLSs, a common disadvantage of the aforementioned methods is the assumption that TPM used is precisely known as a prior. It is well known that transition probabilities (TPs) are introduced to depict the uncertainties of transitions and considered as an essential class of system parameters. The accuracy of TPs is the key in applying JMLSs to practical applications and using inappropriate TPs may lead to performance degradation, especially in the multiple-model estimators. In reality, unfortunately, TPs are generally determined by physical experiments or numerical simulation, and only the estimated values or even incorrect ones are available [17]. In fact, the attention of researchers has been paid on unknown TPs of a simple binary Markov chain since 1970s, and an approximate TPM estimator was derived based on the Bayesian approach [18]. Generally, the existing efforts on unknown or uncertain TPs can be roughly divided into two branches. One is to design effective TPM estimation algorithms. Related results are ranged from truncated maximum likelihood estimation [19], online Bayesian estimation algorithms [20], Kullback–Leibler divergence based approach [21], to novel maximum likelihood method [22]. The other is to design state estimators that are robust to unknown TPs. For example, with the usage of Bayesian methodology, Doucet and Ristic [23] integrated unknown TPs following the Dirichlet distribution analytically to form the desired marginal posterior densities. In [24], the skew truncated Gaussian probability density functions (PDFs) have been proposed to portray uncertain TPs. Besides, another approach is to design robust state estimators against unknown TPs using the so-called H_∞ technique, which is a completely different method with Bayesian technique; see, for example, [25–28].

Certainly, the methods introduced above provide efficient and practical tools to deal with the filtering problems of respective systems. However, most existing estimation algorithms for JMLSs with unknown TPs or partially unknown TPs are obtained using the guaranteed-cost technique. That is to say, state estimators are designed by ensuring that the dynamics of estimation error is upper bounded by a certain constant for the admissible uncertainties. As certain linear matrix inequality existence conditions should be guaranteed at every time step, these estimators may not be easily realized recursively [29]. As specified by Jilkov and Li in [20], on the other hand, online state estimators of JMLSs with unknown TPs can be developed by applying a feasible recursive TPM estimator to Bayesian state estimation algorithms (including but not limit to IMM) straightforwardly. In other words, all the recursive TPM estimation methods mentioned above can be employed to handle the problem considered. However, embedding a TPM estimator into state estimation may double or even triple the computational load, as TPM estimator requires high computational complexity. In addition, the convergence accuracy of TPM estimator is scenario-dependent. The assumption that TPs are time-invariant is