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Online state estimation for discrete nonlinear dynamic systems with nonlinear noise and interference

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Abstract

This paper presents a real-time recursive state filtering and prediction scheme (*PR*) for discrete nonlinear dynamic systems with nonlinear noise and random interference, such as undesired random jamming or clutter. The *PR* is based upon discrete noise approximation, state quantization, and a suboptimal implementation of multiple composite hypothesis testing. The *PR* outperforms both the sampling importance resampling (*SIR*) particle filter and auxiliary sampling importance resampling (*ASIR*) particle filter; whereas Kalman-based nonlinear filters are, in general, inadequate for state estimation of many nonlinear dynamic systems with nonlinear noise and interference. Moreover, the *PR* is more general than grid-based estimation approaches. It is also very suitable for state estimation with either constraints imposed on state estimates or missing observations.

1. Introduction

State estimation is encountered in many areas such as control engineering, chemical engineering, telecommunications, radar tracking, environmental systems, and economics. Many systems in practical applications are more accurately described by nonlinear models. These models can be nonlinear functions of non-Gaussian noise and interference, representing undesired random signals such as jamming or clutter. Since the original work of Kalman [17,18], which introduces the

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Kalman filter for linear models, extensive research has been going on nonlinear state estimation; but an optimal nonlinear estimation approach, which can be used for applications, has not been presented yet for all nonlinear models, except for certain classes of nonlinear models; on the other hand, different suboptimal nonlinear estimation approaches have been proposed in the literature [1–11,13–27,29]. These suboptimal approaches produce estimates by using some sorts of approximations for nonlinear models. The performances and implementation complexities of these suboptimal approaches surely depend upon the types of approximations which are used for nonlinear models. Model approximation errors are an important parameter which affects the performances of suboptimal estimation approaches. The performance of a nonlinear suboptimal estimation approach is better than the other estimation approaches for specific models considered, that is, the performance of a suboptimal estimation approach is model and parameter-dependent.

The most commonly used recursive nonlinear estimation approaches are, currently, particle filters and the Kalman-based nonlinear filters, such as the extended Kalman filter (EKF) [16,29], unscented Kalman filter (UKF) [16,29], and cubature Kalman filter (CKF) [1,15]. Kalman-based nonlinear filters are, in general, Gaussian approximation filters based upon the Gaussian assumption of the probability density functions [15]. That leads to Kalman predictor–corrector framework. Particle filters and the nonlinear estimation approaches presented in [5–10] have been developed for nonlinear models with nonlinear noise (Gaussian or non-Gaussian noise). Particle filters approximate *a posteriori* densities by a large set of weighted and randomly selected points (called particles) in the state space [2,11,25]. In the nonlinear estimation approaches presented in [5–10]: The disturbance noise, interference, and initial state are first approximated by a discrete noise, a discrete interference, and a discrete initial state whose distribution functions approximate the distribution functions of the disturbance noise, interference, and initial state best; states are quantized; and then (composite) multiple hypothesis testing is used for state estimation; whereas grid-based estimation approaches approximate *a posteriori* densities by discrete densities, which are determined by predefined gates (cells) in the predefined state space; if the state space is not finite in extent, then some truncation of the state space is necessitated; and grid-based estimation approaches assume the availability of the state transition density $p(x(k)|x(k-1))$, which may not be easily calculated for state models with nonlinear disturbance noise [2,25]. The nonlinear estimation approaches presented in [5–10] are more general than grid-based approaches since (1) the state space needs not to be truncated, (2) the state transition density is not needed, and (3) state models can be any nonlinear functions of the disturbance noise.

In this paper, an online recursive nonlinear state filtering and prediction scheme is proposed for nonlinear dynamic systems with nonlinear noise and interference representing a random signal such jamming or clutter. The proposed estimation scheme (PR) is an online estimation scheme which also prevents some state estimate divergences caused by the estimation approaches presented in [5–7] for nonlinear dynamic systems with nonlinear noise and interference, whereas the estimation schemes in [9,10] were developed for nonlinear discrete dynamic models without interference. The *PR* is based upon first approximating the disturbance noise, initial state, and interference with a discrete random disturbance noise, discrete initial state, and discrete interference; then quantizing the state, that is, representing the state model with a time varying state machine; and then an online suboptimal implementation of multiple composite hypothesis testing. Quantization of a state is accomplished by dividing the range space of the state into generalized rectangles called gates. The state model of Eq. (1) is only used in order to calculate transitions from gates to gates. If these transitions are somehow available, the state model is not needed for state estimation with the *PR*, whereas the state model is absolutely necessary for state estimation with particle filters.