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Decentralized estimation of overflow losses in a hopper dredger

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Abstract

The Kalman filter and its nonlinear variants have been widely used for filtering and state estimation. However, models with severe nonlinearities are not handled well by Kalman filters. Such a case is presented in this paper: the estimation of the overflow losses in a hopper dredger. The overflow mixture density and flow-rate have to be estimated based on noisy measurements of the total hopper volume, mass, incoming mixture density and flow-rate. In order to reduce complexity and make the tuning easier, a decomposition of the nonlinear process model into two simpler subsystems is proposed. A different type of observer is considered for each subsystem—a particle filter and an unscented Kalman filter. The performance is evaluated for simulated and real-world data and compared with the centralized setting for four combinations of the particle filter and the unscented Kalman filter. The results indicate that the distributed observer achieves the same performance as the centralized one, while leading to increased modularity, reduced complexity, lower computational costs and easier tuning.

Keywords: State estimation; Nonlinear systems; Nonlinear observers; Kalman filter; Particle filter

1. Introduction

Many problems require the estimation of states and possibly uncertain parameters based on a dynamic system model and a sequence of noisy measurements. Dynamic systems are usually modeled in the state-space framework, using a state-transition model, which describes the evolution of states over time and a measurement model, which relates the measurement to the states. These models can be deterministic as well as stochastic.

The most well-known and widely used probabilistic estimation methods are the Kalman filter (KF) and its extension to nonlinear systems, the extended Kalman filter (EKF) (Kalman, 1960; Welch & Bishop, 2002). However, these methods have severe limitations and may become unstable even for linear processes. The unscented Kalman filter (UKF), introduced by Julier and Uhlmann (1997), overcomes some of these deficiencies. The estimates obtained by the UKF are in general more accurate, since the filter does not rely on linearization, but uses directly the nonlinear state-transition function. Its superior performance has been reported in several publications (Hovland et al., 2005; Li, Zhang, & Ma, 2004; Stenger, Mendonça, & Cipolla, 2001; van der Merwe & Wan, 2003). Though more accurate and reliable than the EKF, the UKF still assumes a unimodal distribution of the states and the handling of multimodal distributions remains problematic.

Over the last years, particle filters (PFs) (Arulampalam, Maskell, Gordon, & Clapp, 2002; Doucet, Godsill, & Andrieu, 2000) have been extensively studied. These filters have been successfully applied to state-estimation problems, mainly in the field of target tracking (Hue, Le Cadre, & Perez, 2002; Li et al., 2007; Nait-Charif & McKenna, 2004; Sullivan, Blake, Isard, & MacCormick, 2001). The basic idea behind this technique is to represent probability densities by a set of samples. In this way, a wide range of probability densities can be represented, allowing the handling of nonlinear, non-Gaussian dynamic systems. However, this representation comes with a higher computational cost,

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which may render the filter unusable for on-line or real-time estimation.

Since the above-mentioned methods are suboptimal, their performance varies, depending on the application considered. While for a highly nonlinear and non-Gaussian model, a PF is likely the best option, UKF may also yield good performance with considerably lower computational costs. However, the design of an observer for a complex nonlinear system for on-line estimation is problematic due to tuning difficulties and large computational costs.

Decentralized estimation has been studied in the context of large-scale processes and distributed systems. The architecture in general takes the form of a network of sensor nodes, each with its own processing facility. In case of a fully decentralized system, computation is performed locally and communication occurs between any two nodes. Each node shares information with other nodes and computes a local estimate. Computation and communication is distributed over the network so that a global estimate can be computed. Several topologies have been proposed, depending on the particular application. In case of large-scale processes (Vadigepalli & Doyle, 2003a, 2003b), the network is in general in a hierarchical form, with several intermediate and one final fusion node. For distributed systems, such as multiagent societies (López-Orozco, de la Cruz, Besada, & Ruipérez, 2000; Roumeliotis & Bekey, 2002; Schmitt, Hanek, Beetz, Buck, & Radig, 2002), several fusion nodes exist, which process the data and send the information to the rest of the nodes. Observers for distributed estimation include, but are not limited to decentralized KF and EKF filter (Durrant-Whyte, Rao, & Hu, 1990), information filter and PFs (Bolic, Djuric, & Hong, 2004; Coates, 2004).

In this paper, it is proposed to decompose a nonlinear system model into cascaded subsystems, with the possibility of using different estimation methods for the subsystems. Many nonlinear systems can be represented as cascaded, observable subsystems, which alone are less complex than the original system. Separate observers can be designed for the individual subsystems. Moreover, different types of observers can be combined, depending on the complexity and nonlinearity of the subsystems. This setting can be regarded as a cooperative multiagent system. Each agent has the task of observing one of the subsystems, possibly using different methods and relying on its own measurement and the information gathered from other agents. In turn, each agent communicates its own results to other agents.

The proposed distributed observer design is applied to the estimation of the overflow losses in a hopper dredger. The estimation of overflow losses is an essential step toward the optimization of the separation process in the hopper, which is of vital importance for future improvement in dredging efficiency, accuracy and from the viewpoint of labor saving. In the considered process, the measured variables are heavily corrupted by noise. The system is highly nonlinear, and for global state estimation a PF would be required. However, the model can be represented as two cascaded subsystems, which allows the use of two observers. For these observers the combinations of UKF and PF are considered and the four possible combinations in the distributed setting are compared with the performance of a centralized PF for the whole system, both on simulated and experimental data.

The structure of the paper is as follows. Section 2 reviews the UKF and the PF methodology. In Section 3, the proposed cascaded observer setting is given, while Section 4 presents the dynamic sedimentation model and the models used for estimation purposes. Sections 5 and 6 give the results for the simulated and experimental data, respectively. Finally, Section 7 concludes the paper.

2. Estimation methods

In this section, two methods for estimating the states and parameters of a nonlinear system are presented. Consider the following discrete-time, possibly time-varying, nonlinear system:

$$x_k = f(x_{k-1}, v_{k-1}), \tag{1}$$

$$y_k = h(x_k, \eta_k), \tag{2}$$

where k is the current time step, x the state variables, v, η the noises of known distributions, y the measurements, f the state transition model, h the measurement model.

Note that the functions f and h may also depend on other known inputs or parameters. However, for the ease of notation, these variables are omitted. It is assumed that system (1)–(2) is observable, in order to be able to estimate the states.

The goal is to estimate the states of interest. Two methods are considered: the UKF and the PF. Both methods use notions from probability theory, however, the UKF is a deterministic method, while PFs are stochastic. Both filters are recursive algorithms, that use all the provided information (model and observations) to estimate the current state of the system. The filters work in two steps: prediction and update. The *prediction* step uses the system model and the information incorporated so far in order to predict the process' states. This stage is also known as the time update step, as it projects the current state forward in time. The *update* stage uses the latest measurement to modify (correct) the projected state. This stage is also known as measurement update, since it incorporates the information brought by the new measurement.

2.1. Unscented Kalman filter

For linear systems corrupted by white Gaussian noise, the KF is proven to be an optimal filter in the least mean square sense. For nonlinear systems, several extensions exist: the EKF (based on linearizing the models around the current states), and the family of sigma point KFs (Julier & Uhlmann, 2002b; van der Merwe, 2004).