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Research article

Robust particle filter for state estimation using measurements with different types of gross errors

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ABSTRACT

For industrial processes, the state estimation plays a key role in various applications, such as process monitoring and model based control. Although the particle filter (PF) is able to deal with nonlinear and non-Gaussian processes, it rarely considers the influence of measurements with gross errors, such as outliers, biases and drifts. Nevertheless, measurements of dynamical systems are often influenced by different types of gross errors. This paper proposes a robust PF approach, in which gross error identification is used to estimate magnitudes of gross error. The gross errors can be removed or compensated so that a feasible set of particle sampling can contain the true states of the system. The proposed robust PF approach is implemented on a complex nonlinear dynamic system, the free radical polymerization of styrene. The application results show that the proposed approach is an appealing alternative to solving PF estimation problems with measurements containing gross errors.

1. Introduction

In today's competitive process industries, there is intense pressure to improve the performance of process facilities. However, due to various causes such as sensor reading errors, sensor failures, and sensor unavailability, real-time information about critical process variables is often unavailable. In such cases, extracting useful hidden variable information using measured variables and process models becomes more and more important to sustain plant safety, productivity and profitability. The ideal approach to estimating the unobserved states of a dynamic system with a given noisy observation of the process can be considered as an optimal filtering problem within a Bayesian framework. As the core of the state estimation tools, filters have been developed from frequency domain to time domain, from non-recursion to recursion, and from non-stationary random process to the state space model. Nowadays, there are several filter techniques for state estimation, such as Kalman filter (KF), extended KF (EKF), unscented KF (UKF) and particle filter (PF).

KF was first described and partially developed in technical papers by Kalman [1,2]. The algorithm keeps track of the estimated state of the system and the variance or uncertainty of the estimate. The estimate is updated using a state transition model and measurements. Jazwinski proposed EKF by extending the use of KF to nonlinear dynamic systems [3]. EKF assumes a Gaussian posterior density and adopts the first-order Taylor series expansion to provide a local approximation for the current state. UKF uses a series of determined samples to approximate the posteriori probability density of the state, and it has a good tracking performance for any nonlinear system in the Gaussian environment [4]. Still, the above methods have some limitations. KF is limited to the linear systems with Gaussian noise. EKF relies on linearization. The accuracy of estimates and the tuning of EKF strongly depend on the accuracy of linearization. Thus, EKF is not suitable for the highly nonlinear system. UKF improves the accuracy of EKF and provides significant improvements over EKF estimates, but it is still limited to the assumption of Gaussian noise.

During the past decade, given a series of related observations, the PF technique has become a popular signal processing tool for problems that involve nonlinear tracking of an unobserved signal of interest [5–8]. PF is a class of Monte Carlo simulation-based filtering methods for nonlinear/non-Gaussian systems, leading to computational intractability of traditional methods. It does not assume a fixed shape of any probability density; instead, it approximates the conditional density by a finite number of particles/samples and let these particles propagate in a certain way to mimic the evolution of the conditional density. The approximated conditional density converges to the true conditional density as the number of particles increases to infinity. Because PF can

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capture the time-varying nature of distributions in nonlinear dynamic systems; PF has been widely used for state estimation in many fields recently.

Chen et al. used PF for dynamic data reconciliation and process change detection [9]. They also applied PF and the kernel smoothing method on-line for state and parameter estimation in a highly non-linear batch process [10]. Rigatos applied PF and KF for state estimation and control of DC motors, and pointed out that PF could succeed in accurately estimating the motor's state vector, but at the same time it required higher computational effort [11]. López-Negrete et al. used the constrained PF approach to approximate the arrival cost in moving horizon estimation, and applied the method in the continuously stirred tank reactor and the constrained batch reactor process in order to estimate the unmeasured states accurately [12]. Dou and Li used interactive multiple model and PF for robust visual tracking [13]. Ding et al. used PF framework with local structural manifold learning for object tracking [14]. Havangi proposed a robust evolutionary PF, which did not require prior knowledge about the system [15]. Yin and Zhu proposed an intelligent PF for state estimation and fault detection of nonlinear systems. The intelligent PF is derived from the genetic algorithm to further improve the particle diversity [16]. A construction method for a state feedback control system using PF as an observer for probabilistic state estimation was described and verified experimentally by Nishida [17]. Svečko et al. (2015) presented a PF algorithm for distance estimation using multiple antennas on the receiver's side and only one transmitter, where a received signal strength indicator of radio frequency was used [18]. Most of those approaches specifically focused on state estimation and/or parameter estimation. They do not explicitly consider the rectification of measurements which may be affected by gross errors.

Most of the PF based methods presume that the corrupted measurements are free of gross errors or, more specifically, that the measurements only contain zero-mean random noise so that good state estimation can be derived. Nevertheless, measurements often suffer from sudden large disturbances (outliers), systematic significant biases or slow drifts. If measurements with those types of gross errors are used for state estimation, the performance of the PF based methods would be significantly degraded. The measurements with gross errors should not be treated in the same way as the regular measurements [19].

Only a few studies [7,9,19,20] discussed how to treat the measurements with gross errors in a particular way to improve the performance of PF. Zhang & Chen (2014) proposed a novel PF algorithm based on the measurement test to solve the dynamic simultaneous data reconciliation and gross error detection problem. When there are outliers in the measurements, PF can also effectively solve the data reconciliation and gross error detection problem to derive accurate estimated states and reconciled measurements in the nonlinear dynamic process systems [19]. Other researchers also considered the presence of outliers in the measurements and proposed strategies to detect and decrease the influence of outliers on the results of state estimation [7,9]. However, if the gross errors are constantly present in the measurements, such as drifts and systematic biases, those gross errors will lead to the degeneration of the filter. Zhao et al. (2014) proposed a constrained PF approach to state estimation, which involved three alternative strategies to impose the constraints on the prior particles, posterior particles, and state estimation. The method made a balance between the prior and the likelihood functions by adjusting the weights of the violated and the valid particles, respectively [21]. They also applied PF to state estimation in batch processes based on a two-dimensional state-space model [22]. Du et al. proposed a novel PF algorithm for target tracking in the presence of glint noise based on observation noise modeling [23]. Anwar et al. mentioned that the PCA based blind attack modeling cannot be guaranteed if the measurement data contains any gross errors. They proposed a technique based on sparse optimization that can overcome this limitation by separating the gross errors from the measurement matrix [24]. Based on cascaded Kalman-Particle Filtering, Nargess et al. proposed a gyroscope drift and robot attitude estimation method and applied it to a 3D camera system [20]. However, they only considered one type of gross error without simultaneously considering different types of gross errors, such as outliers, systematic biases, and drifts.

The challenges of considering different types of gross errors in PF based state estimation are how to model each type of gross error, how to identify and estimate gross errors (especially the biases and drifts) and how to compensate the measurements in the procedures of PF algorithms. To solve the problem of considering different types of gross errors and to enhance the performance of PF, the objectives of this work are

(1) to construct the general model structure with different types of gross errors;
(2) to develop the identification and estimation scheme of gross errors from the corrupted measurements;
(3) to combine the estimated gross errors with PF to make a robust PF algorithm that can handle measurements in the applications with different types of gross errors.

The rest of the paper is organized as follows. The preliminary of the generic PF for state estimation is briefly reviewed in the next section. The formulations of measurements with random errors as well as various types of gross errors are presented in Section 3. In Section 4, the robust PF scheme, including gross error identification and measurement compensation, is proposed to improve particle sampling. Considering different types of gross errors in measurements in the case study for free radical polymerization of styrene, the effectiveness and the advantages of the proposed robust PF for state estimation are demonstrated in Section 5. Finally, in Section 6, conclusions and future works are discussed.

2. Preliminary of PF for state estimation

A typical dynamic process system with the state dynamics and the measurement equations is given by

$$\mathbf{x}_k = \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}) + \mathbf{v}_{k-1} \quad (1)$$

$$\mathbf{z}_k = \mathbf{h}(\mathbf{x}_k, \mathbf{u}_k) + \mathbf{w}_k \quad (2)$$

where $\mathbf{x}_k \in R^{N_x}$ is the vector of states to be estimated and k denotes the time step. N_x is the dimension of the vector of states. $\mathbf{f}$: $R^{N_x} \to R^{N_x}$ is the nonlinear transition function, which defines the evolution of the vector of states as a first-order Markov process. $\mathbf{h}$: $R^{N_x} \to R^{N_z}$ is the measurement function, which defines the relationship between the vector of states $\mathbf{x}_k$ and the vector of measurements $\mathbf{z}_k \in R^{N_z}$. N_z is the dimension of the vector of measurements. $\mathbf{u}_k$ is the vector of inputs. $\mathbf{v}_{k-1} \in R^{N_x}$ and $\mathbf{w}_k \in R^{N_z}$ are the white noise sequences for the process states and measurements. They are independently and identically distributed according to the probability density functions (PDFs) $p_{\mathbf{v}}$ and, $p_{\mathbf{w}}$ respectively. The PDFs $p_{\mathbf{v}}$ and $p_{\mathbf{w}}$ are usually assumed to be Gaussian; i.e. $\mathbf{v}_{k-1} \sim G(\mathbf{v}_{k-1}; \mathbf{0}, \mathbf{\Psi})$ and $\mathbf{w}_k \sim G(\mathbf{w}_k; \mathbf{0}, \mathbf{\Sigma})$, where $\mathbf{\Psi}$ and $\mathbf{\Sigma}$ are the covariance matrices.

The system defined by Eqs. (1) and (2) can then be alternatively presented in a probabilistic form