Computers and Electrical Engineering 57 (2017) 118–133

Contents lists available at ScienceDirect

Computers and Electrical Engineering

journal homepage: www.elsevier.com/locate/compeleceng

Sensor and actuator bias estimation using multi model approach☆

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ARTICLE INFO

Article history:
Received 3 October 2016
Revised 1 November 2016
Accepted 1 November 2016
Available online 9 November 2016

Keywords:
Kalman filter
H– infinity filter
Process monitoring
Actuator bias
Sensor bias
Conical tank process
CSTR process

ABSTRACT

The objective of this paper is first to design an Adaptive Linear Kalman Filter (ALKF) to estimate nonlinear process states and to compare the performance of the ALKF with the Extended Kalman Filter (EKF). The designed ALKF is next used to detect sensor and actuator biases which may occur either sequentially or simultaneously using a Multi Model ALKF (MMALKF). Finally the Multi Model Adaptive Linear H^{∞} Filter (MMALH$^{\infty}$F) is designed to increase the robustness of bias Detection in the presence of unknown noise statistics and unmodeled dynamics. The proposed estimator is demonstrated on the variable area tank process and Continuously Stirred Tank Reactor (CSTR) process to show its efficacy.

1. Introduction

Sensors give an exact view of the process to controllers and operators; actuators implement controller action to meet the design requirements. In the presence of bias either in the sensor or in the actuator, although the controller is robust against unmodeled dynamics and disturbances, the process performance will not be good. If the controller is designed with fault tolerance, then it is possible to get optimal performance irrespective of faults in the equipment. Model based Fault Detection Diagnosis works in the concept of analytical redundancy, which uses mathematical relation between the process and measured variables. Kalman Filter (KF) finds wide applications in process industries because of its optimal and recursive nature. In the presence of known process and measurement noise statistics and with moderate plant-model mismatch the KF is the best linear state estimator. But most of the process plants are nonlinear in nature so the nonlinear version of the KF that is EKF is widely used in process industries because of their simplicity.

In 2011 Villez et al. [1] investigated the application of the KF and the EKF for FDD in a nonlinear buffer tank system. The performance of the KF was found to be good for linear version of the process and its estimation diverges for the nonlinear version. In 2009, Qu et al. [2] investigated the performance of a Linear Kalman Filter (LKF), an EKF and an Unscented Kalman Filter (UKF) using CSTR and batch reactor. These have shown that the performance of the EKF and the UKF are comparable when the process nonlinearities are mild. In the presence of severe nonlinearities and large measurement noise levels the UKF outperforms EKF. In 2013 Castillo et al. [3] proposed a method to predict the transient behavior of the residual to detect and isolate faults. This method uses the EKF for state estimation and residuals are generated by comparing the measured

☆ This paper is for CAEE special section SI-sdc. Reviews processed and recommended for publication to the Editor-in-Chief by Guest Editor Dr. R. Bestak.

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http://dx.doi.org/10.1016/j.compeleceng.2016.11.003

and the estimated values. In 2012 Lim et al. [4] proposed an analytical redundancy based multiple hypothesized filters to identify satellite actuator faults in an LEO satellite. The proposed structure consists of multiple hypothesized Kalman Filter with different fault models. The failure probabilities are estimated from the filter residuals and the master filter finds the best estimation from weighted sum of probabilities. Dashpande et al. [5] in 2008, have proposed a multiple operating point approach to represent a nonlinear process.

1.1. Fault detection using multiple model approach

To detect and diagnose multiple faults, deployment of bank of Kalman Filters has been investigated by Menke et al. in 1995, Hanlon et al. [6,7] in 2000. This approach uses multiple KFs and each KF is designed with different fault hypothesis. In 2014 Lu et al. [8] proposed a new method to improve the performance of Multiple Model Adaptive Estimation (MMAE). To improve the estimation accuracy the authors used the UKF instead of the KF and the EKF. In addition to this they added a reinitialisation algorithm to eliminate false alarms and they showed an improved performance when compared to existing MMAE and Interacting Multiple Model (IMM) using the proposed Selective Reinitialisation MMAE (SRMMAE). In 1996, Eide et al. [9] implemented the MMAE algorithm to isolate multiple sensor and actuator faults, and implemented using Variable In-flight Stability Test Aircraft (VISTA) F-16 flight software simulation. The authors used a bank of KFs and each KF was modeled to estimate a particular sensor and actuator fault. In 2008 Heredia et al. [10] investigated the implementation of dedicated observer scheme for fault detection and diagnosis in autonomous helicopters. The number of KFs used was equal to the number of outputs being measured. Each estimator residual is generated by all system inputs and one output. Occurrence of fault in a particular sensor will affect a KF to which that sensor output is connected. In 2003 Kobayashi, T., et al. [11] investigated the application of bank of augmented KF to isolated sensor and actuator faults. They showed the improved performance of designed multiple model estimators using nonlinear aircraft engine simulation in the presence of a degraded system condition. To isolate sensor and actuator faults nonlinear version of Generalized Likelihood Ratio (GLR) method using local linear models has been used.

1.2. H^∞ filter using game theory approach

To improve the performance of a KF in the presence of unknown noise statistics and unmodeled dynamics the H^∞ Filter using game theory approach has been developed by, Banavar et al. in 1991, Yaesh et al. in 1992 [12–13]. In 1997 Shen et al., [14] compared the performance of an H^∞ filter and the LKF in the presence of unknown noise statistics and unmodeled dynamics using damped harmonic oscillator, and showed an improved performance in estimating the system state. In 2013 Hou et al. [15] proposed a weighted sum of H infinity filter to improve target tracking in the presence of unknown measurement noise statistics and jamming information. The H infinity filter showed better tracking performance compared to Gaussian sum EKF. In 2013 Lim [16] proposed a Cost Reference Particle Filter (CRPF) and compared the performance of the H^∞ Filter, CRPF and EKF in target tracking system. The simulation results showed that for the implementation of EKF, knowledge about the noise statistics is needed and for highly nonlinear system CRPF performance is better compared to H^∞ Filter. In 2012 Guo et al. [17] compared the performance of the EKF and the H^∞ Filter in the presence of modeling errors in military guidance target tracking system. The simulation results show that the tracking performance of the H^∞ Filter is better compared to the EKF.

This paper is organized in five sections. The next section deals with the design of the ALKF and ALH$^\infty$F using gain scheduling technique. Section 3 discusses the design of the MMALKF and MMALH$^\infty$F to detect multiple sensors and actuator biases which may occur either sequentially or simultaneously. Section 4 discusses the simulation results. Finally, the conclusion of the entire research contribution of this paper is outlined in Section 5.

2. State estimation using adaptive linear Kalman filter (ALKF) and adaptive linear H^∞ filter (ALH$^\infty$F)

2.1. Design of Kalman filter for the local linear models of a nonlinear process

To estimate nonlinear process states using KF, the nonlinear process is first linearized around a nominal operating point. After linearizing the nonlinear process, KF is designed for the linearized model.

Let the nonlinear DT stochastic process be given by the following state and measurement equations.

$$x(k) = f(x(k-1), u(k-1), d(k-1)) + w(k) \tag{1}$$

$$y(k) = h(x(k), u(k), d(k)) + v(k) \tag{2}$$

where, $x \in R^n$ represents the state variables, $u \in R^m$ represents the known input variables, $d \in R^q$ represents an unknown input variables, $y \in R^p$ represents the measured output variables and $w \in R^r$ and $v \in R^p$ represents the process and measurement noise respectively. It is further assumed those $w(k)$and$v(k)$ are zero mean mutually uncorrelated Gaussian white noise sequences with covariance M and N respectively and k represents sampling instant.

The state space model of the stochastic process around a nominal operating point $\bar{x}$ is given by,

$$x(k) = \Phi_x(x(k-1) - \bar{x}) + \Phi_u(u(k-1) - \overline{u}) + \bar{x} + w(k-1) \tag{3}$$