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A practical note on evaluating Kalman filter performance optimality and degradation

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Abstract

This paper presents useful remarks to the readers on the Kalman filter (KF) performance optimality, degradation, and some innovation related parameters. Guidelines for efficient approach for evaluation of the KF performance optimality and sensitivity analysis are presented. Performance degradation due to uncertainty in process and measurement noise statistics is discussed. Consistency check between the filter-calculated covariances versus actual mean square errors are provided, which can be used not only as a verification procedure for the filtering correctness, but also as a approach for making trade-off in designing a suitable Kalman filter. In addition to numerical algorithms, useful Matlab programs are accompanied where necessary to the readers for getting better insight in practical implementation. Exploration of the behaviour of some innovation based parameters useful in adaptive filter and system integrity designs, including covariance of innovation sequence, degree of mismatch (DOM), and degree of divergence (DOD), etc., is also involved.
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1. Introduction

The Kalman filter (KF) [1–3] is commonly used to estimate the system state variables and suppress the measurement noise. It has been applied in the areas as diverse as aerospace, marine navigation, radar target tracking, control systems, manufacturing, and many others. Studying the operation of the Kalman filter leads to an appreciation of the inter-disciplinary nature of system engineering. The Kalman filter not only works well in practice, but also it is theoretically attractive because it has been shown that it is the filter that minimizes the variance of the estimation mean square error (MSE).

In Kalman filter designs, the divergence due to modeling errors is critical. The implementation of Kalman filter requires that the complete a priori statistical knowledge of the process noise and measurement noise are available. Poor knowledge of the noise statistics may seriously degrade the Kalman filter performance, and even provoke the filter divergence. If the theoretical behaviour of a filter and its actual behaviour do not agree,

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divergence problems will occur. That is, if the Kalman filter is provided with information that the process behaves a certain way, whereas, in fact, it behaves a different way, the filter will continually intend to fit an incorrect process signal. When the measurement situation does not provide sufficient information to estimate all the system state variables, then the estimation error covariance matrix becomes unrealistically small and the filter disregards the measurement. When apparent divergence occurs, the actual estimate error covariance remains bounded, but it approaches a larger bound than the predicted error covariance; when true divergence occurs, the actual estimation covariance eventually becomes infinite.

In various circumstances where there are uncertainties in the system model and noise description, and the assumptions on the statistics of disturbances are violated due to the fact that in a number of practical situations, the availability of a precisely known model is unrealistic since in the modelling step, some phenomena are disregarded. The suboptimal configuration is typically based on a simplified error state dynamic/measurement model. One way to take them into account is to consider a nominal model affected by uncertainty. Covariance analysis is a common tool to provide numerical histories depicting the accuracy of a given configuration in terms of the covariance of its associated error state vector. Therefore, the analysis can be used to evaluate the performance of the suboptimal filter that operates in a real world environment, and can be utilized as a basic design tool during the synthesis and test of the suboptimal configuration.

To fulfil the requirement of achieving the filter optimality, an adaptive Kalman filter (AKF) [4–7] can be utilized as the noise-adaptive filter for tuning the noise covariance matrices. Adaptive filters are based on dynamically adjusting the parameters of the supposedly optimum filter based on the estimates of the unknown parameters. Adaptive Kalman filters can be based on an on-line estimation of motion as well as the signal and noise statistics available data. Many efforts have been made to improve the estimation of the covariance matrices based on the innovation-based estimation approach. The two major approaches that have been proposed for AKF are multiple model adaptive estimate (MMAE) and innovation adaptive estimation (IAE). The innovation sequences have been utilized by the correlation and covariance-matching techniques to estimate the noise covariances. The basic idea behind the covariance-matching approach is to make the actual value of the covariance of the residual consistent with its theoretical value. The IAE approach coupled with fuzzy logic techniques with membership functions designed using heuristic method has been very popular to adjust the noise statistics [8–10].

Any practical data fusion system is susceptible to faults that may lead to violations of estimate consistency. Robustness to such faults is necessary to maintain the integrity of the information in the system. Statistical decision tools for detecting abrupt changes in the properties of stochastic signals and dynamical systems have numerous applications, from the on-line fault detection in complex technical systems to detection of signals with unknown arrival time in radar and sonar signal processing. The main goal of the sensor fault detection is to detect the system degradation when it leads to an unacceptable growth of the output errors [11,12].

Several practical issues regarding the Kalman filter performance optimality and degradation will be presented for conveying some important phenomena to the readers. Content of discussion covers performance degradation due to uncertainty in process and measurement noise statistics, consistency check between the filter-calculated covariances versus actual mean square errors, and behaviour for some innovation related parameters. The remarks presented in this paper are beneficial to the Kalman filter designers, which can be employed as guidelines for developing a suitable filter configuration, and can provide useful information in the adaptive Kalman filter and system integrity design.

This paper is organized as follows. In Section 2, practical notes on Kalman filter and arbitrary gain suboptimal filter are pointed out. In Section 3, Kalman filter solution and optimality evaluation is presented. Performance degradation due to uncertainty in process noise is discussed in Section 4. In Section 5, performance degradation due to uncertainty in measurement noise is presented. The conclusion is given in Section 6.

2. Kalman filter and arbitrary gain suboptimal filter

2.1. Continuous Kalman filter

Consider a dynamical system whose state is described by a linear, vector differential equation. The process model and measurement model are represented as

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