Aerospace Science and Technology 50 (2016) 88–95

Contents lists available at ScienceDirect

Aerospace Science and Technology

www.elsevier.com/locate/aescte

Window based Multiple Model Adaptive Estimation for Navigational Framework

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ARTICLE INFO

Article history:
Received 3 July 2015
Received in revised form 1 November 2015
Accepted 23 December 2015
Available online 29 December 2015

Keywords:
Adaptive Kalman filter
Optimal state estimation
AHRS
Innovation Adaptive Estimation
Multiple Model Adaptive Estimation

ABSTRACT

Kalman filter based algorithms aim at providing accurate estimate of the state parameters which is indirectly governed by the accuracy of the sensor measurement and noise parameters fed to the system model. Multiple Model Adaptive Estimation (MMAE) is one of the adaptive techniques which tries to reduce the dependency of Kalman filter on the noise parameters fed to the system. The main goal of this work is to improve state estimation by incorporating window size as one of the unknown parameters in MMAE framework, referred to as Window based MMAE (WMMAE). The proposed scheme intertwines the concepts of Innovation Adaptive Estimation (IAE) and MMAE in one structure and the state estimation for each model is implemented by IAE. Simulation results prove the efficacy of WMMAE scheme as compared to MMAE and its other variants.

1. Introduction

Inertial navigation system (INS) is one of the main building blocks of today's guidance and control systems in most of the vehicles determining its attitude and positional information [1]. It uses different sensors such as accelerometer, gyroscope, and magnetometer [2] for obtaining angular orientation and position of the moving object with respect to an inertial frame of reference [3]. These navigation systems require optimal state estimation schemes for reducing the effect of time varying noise embedded in the sensor output.

Kalman filtering is one of the most widely used techniques for state estimation and it has undergone several improvements over time since its introduction in 1960 by R.E. Kalman [4]. The most needed improvement to the simple Kalman filter was a non-linear extension of it that is popularly known as Extended Kalman Filter (EKF) [5]. EKF uses Taylor series [6] approximation for applying Kalman filter to nonlinear systems. Though the EKF framework performs better than other filtering techniques, a major limitation with it is the requirement of an accurate noise parameter estimate to be provided *a priori*. Inertial sensors being prone to time varying bias and drift leads to a change in these noise parameters with time. Thus, a constant noise parameter assumption over the complete flight duration is not rational and leads to less accurate state estimation [7]. This, thus necessitated researchers to develop schemes by which the noise parameters can be tuned adaptively.

The Kalman filter scheme which changes these noise parameters in-run is referred to as adaptive Kalman filter (AKF). The AKF scheme can be classified into two types depending on the method used for adaptation, i.e., a) Innovation Adaptive Estimation (IAE) [8,9], and b) Multiple Model Adaptive Estimation (MMAE) [10–13]. IAE is an adaptive filtering scheme which uses single EKF with an inbuilt framework to adapt process and measurement noise covariance parameters (Q and R) on the basis of the innovation or the residual sequence. The MMAE methodology instead uses a bank of Kalman filters running in parallel to provide a weighted sum of each individual KF with different α, wherein α is a set of all unknown parameters which varies from one filter to the other. This scheme has received a revived interest among researchers with increasing speed of computational platform over time, which was a bottleneck for implementation of MMAE in the past. Recently, MMAE has found application in different areas [14,15], such as, target tracking [16], fault diagnosis [17,18], bias calibration [19], and navigation [20]. Though the IAE scheme is computationally much simpler than MMAE, it requires the knowledge of system model accurately and an appropriate window size for computing covariance parameter [21]. With unique ability of MMAE to handle parametric uncertainties and non-specific requirement of stochastic parameters in system model [22–24], there have been several advancements towards the MMAE framework in the recent past. For a system model known with high confidence, Q and R are the

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http://dx.doi.org/10.1016/j.ast.2015.12.025
1270-9638/

two main unknown system parameters considered in MMAE formulation [9]. The MMAE framework uses a stack of Kalman filters which have individual estimate at each epoch and resultant output is a weighted sum of each individual filter's estimate [20,25–27]. MMAE works better especially in two conditions, one in which the system model is not known completely [15] and the other in which one needs to select the best model out of given models [25]. The main aim of this work is to devise an MMAE scheme with IAE as the state estimation block instead of EKF and including window size as an additional unknown parameter.

The MMAE scheme can be broadly classified in three different forms: a) Classical MMAE [26], b) Interactive Multiple Model (IMM) [28] and c) MMAE with variable structure [29]. Several modifications have been tried in recent past to improve the existing MMAE [24,30] framework such as β-stripping, probability lower bound, scalar penalty increase, probability smoothing, increased residual propagation [31] and generalized residual MMAE [32]. The exponential term (β) in the MMAE equation plays a very important role in the probability calculation. If two filters have a similar performance in the filter stack, MMAE assigns higher probability to the filter whose β value is relatively larger. This probability eventually tends to 1, and is inconsistent with the actual probability value for each filter, leading to undesirable performance [30]. Maybeck and Stevens [33] and Jia and Xu [34] removed this β term from probability calculation and showed an improvement in the performance of the classical MMAE scheme. On an another direction towards improving MMAE, the magnitude of scalar penalty value 1/2 in the exponential term was proposed to be increased to a larger value, resulting in a faster changing probability values [31]. However, this fast changing probability value leads to excessive competition and needs to be reduced appropriately [20]. Li et al. in [20] proposed a time varying penalty value with an exponential decay to improve the filter performance.

Towards other improvements over MMAE, Maybeck introduced the concept of limiting the likelihood value required for the weight calculation to ε whenever it reaches zero. This avoids the problem of zero weighting factor for any filter, keeping all the filters active in the MMAE loop [35]. The tuning of MMAE filtering scheme has been discussed in [35] wherein the Q and R noise parameters are changed manually, thus affecting the filter's performance significantly. Maybeck and Hanlon introduced the scheme of increased residual propagation in which few update steps of Kalman filtering is skipped after each propagation, reducing system's computational complexity with marginal loss in filter performance [30]. Another modification proposed in the literature includes the concept of generalized residual MMAE wherein the innovation and post fit residual are combined to form a generalized residual for calculating filter's weight [32,36]. Classical MMAE is also improved by using unscented Kalman filter instead of EKF in the filter bank [37,38]. Recently, Xiong et al. have proposed to incorporate robust Kalman filter for the state estimation of each model and shown to provide better convergence as compared to traditional state estimation schemes [15].

Another generation of MMAE, i.e., Interacting Multiple Model Filter [39,40] is a computationally efficient filter which takes the jumps in the system under consideration. This scheme consists of three major steps: interaction (mixing), filtering and combination. In each time step, the initial conditions for certain model-matched filter are obtained by mixing the state estimates produced by all filters from the previous time step [41]. This approach provides an integrated framework for fault detection, diagnosis, and state estimation [42] and has a relatively low computational load [43].

Though these modifications have led to improvements in the core MMAE structure, they do not incorporate the adaptation of Q and R values. The MMAE has limited options for Q and R in its filter bank and may not provide very accurate state estimate for MEMS based system where these values change with time. The IAE scheme has a limitation in terms of the appropriate window size selection for the calculation of noise covariance. The window size used for computing noise covariance in IAE requires a methodology for adapting its window length over time. It is thus hypothesized here to develop a scheme by which MMAE can provide a weighted combination of IAE with different window sizes in its core structure, taking advantage of both the IAE and the MMAE schemes.

In this paper, an intuitive concept of combining the IAE filter with MMAE is proposed to maintain appropriate window length and take advantages of Q and R adaption scheme of IAE. The Window based Multiple Model Adaptive Estimation (WMMAE) scheme considers the window length as an unknown parameter and the IAE filters in the bank have options to choose from different window sizes. Hence, at each time instant the WMMAE will give higher weightage to the filter with lowest residual value [25] and lesser weightage to the ones which do not perform accurately.

2. Mathematical preliminaries

In this article, it is proposed to improve the MMAE based state estimation technique by incorporating IAE and MMAE in a coherent framework with the incorporation of window size as the unknown parameter in MMAE. The basic building block of MMAE is an extended Kalman filter which are stacked together to provide a weighted sum of all KFs. The WMMAE scheme proposed here replaces EKF with IAE and thus the theoretical concepts related to EKF, IAE and MMAE are discussed here for a better comprehension of the ideas proposed in this paper.

2.1. Extended Kalman Filter

The Kalman Filter (KF) proposed in 1960 was designed only for linear systems and required modifications for it to be applied on non-linear physical systems. A non-linear version of the KF uses linearization based on Taylor series expansion and is referred to as Extended Kalman Filter (EKF) [6]. Although various other improvements over KF, like the Unscented Kalman Filter, Particle Filter and H-infinity filter have been developed in the past, EKF is one of the most popular choices due to its computational efficiency.

EKF model varies from continuous to discrete to a hybrid of both and is applied accordingly for system under consideration. In most of the real world applications, the process and measurement dynamics are continuous and discrete in nature respectively, compelling the designer to select a continuous process-discrete measurement EKF model. Such a hybrid system can be described as:

$$\dot{x}(t) = f\left(\vec{x}(t)\right) + \tau_c \vec{w}(t) \tag{1}$$

$$y_k = h(\vec{x}_k) + \vec{v}_k \tag{2}$$

$$E\left[\vec{w}(t)\vec{w}(t-\tau)^T\right] = Q\,\delta(t-\tau) = \begin{cases} Q \rightarrow t = \tau \\ 0 \rightarrow t \neq \tau \end{cases} \tag{3}$$

$$E\left[\vec{v}_k \vec{v}_j^T\right] = R\delta_{kj} = \begin{cases} R \rightarrow k = j \\ 0 \rightarrow k \neq j \end{cases} \tag{4}$$

where $\vec{x}$ is the system state, $f(\bullet)$ is the continuous process dynamics, y_k is the discrete measurement state, $h(\bullet)$ is the measurement mapping function, $w(t)$ is continuous time white noise with covariance Q, and $\vec{v}_k$ is the discrete measurement noise with covariance R.

The details of EKF predictor and corrector equations are not covered here and may be referred to [25] for more details. The EKF scheme suffers from issues such as divergence and performance degradation when Q and R values are not chosen appropriately