Available online at www.sciencedirect.com

ScienceDirect

IFAC-PapersOnLine 49-17 (2016) 076–081

Application of Input and State Multiple Model Adaptive Estimator for Aircraft Airspeed Approximation

Péter Bauer* Tamás Baár* Tamás Péni* Bálint Vanek* József Bokor*

* MTA SZTAKI Systems and Control Lab, Budapest, 1111 Hungary
(corresponding author e-mail: bauer.peter@sztaki.mta.hu)

Abstract: This paper addresses the problem of state estimation in the presence of unknown inputs if the system is dependent on an uncertain parameter. Multiple Model Adaptive Estimation is applied to state and unknown input observers. The theory is evaluated on an aircraft airspeed estimator algorithm. The developed algorithm is based-on linear time invariant (LTI) models of an aircraft linearized at distinct airspeed values. Separate Kalman Filters are designed for aircraft LTI models, run parallel, and the airspeed estimate is the weighted sum of the airspeed estimates provided by the Kalman Filters. Linear and nonlinear test simulations without and with measurement noise proved that the developed algorithm is able to provide accurate airspeed estimates.

Keywords: Kalman Filters, Multiple Model Adaptive Estimation, State and Unknown Input Estimation

1. INTRODUCTION

The unknown state of a given system can be easily determined with a state-observer if the system structure, the inputs and outputs are known and the system is observable. However, in the case of parameter uncertanity the system model cannot be considered to be known, and a further tool is needed to carry out state estimation. One of the most widely studied estimation theory for this problem is the Multiple Model Adaptive Estimation (MMAE) framework which is able to provide state estimation in case of systems with parameter uncertainty. Several papers are available about MMAE and its application onboard an aircraft. For instance Eide and Maybeck (1996) uses MMAE method to detect faulty actuators and sensors and signal it to the pilot, also discussing tuning the filters, and improving accuracy. Lewis (1996) takes the previous idea further as it likewise offers a control redistribution between the remaining surfaces to minimize the loss of control. In Sheldon and Maybeck (1993) one can find a basic design of the MMAE, and Multiple Model Adaptive Regulators to provide stabilizing control considering the uncertain parameter vector. Using MMAE to identify actuator and sensor failures in an aircraft engine is viable as well, as stated in Kobayashi and Simon (2003). Finally, an important performance enhancement of the MMAE was presented in Maybeck and Hanlon (1995) to improve the accuracy and swiftness, and to reduce the false alarms through different modifications. However, these papers do not address the problem of unkown inputs which can have significant effect to the system performance. Gillijns and Moor (2007a) and Gillijns and Moor (2007b) provide a solution for state and unknown input estimation (without and with unknown input direct feedthrough respectively). The goal of this paper is to evaluate the application of a broadend MMAE architecture, where unknown inputs are also estimated based-on Gillijns and Moor (2007b).

In order to extend Control and Guidance functionalities and to make the flying task easier, one possibility of improvement for future aircraft could be the incorporation of analytical redundancy to detect, isolate and estimate sensor faults. The exploited Fault Detection and Isolation (FDI) technique can extend the availability of the sensor measurements without adding new sensors. In the frame of the RECONFIGURE project (see Goupil et al. (2015)) one goal is the development of an airspeed estimator algorithm, which is able to provide accurate airspeed estimation in the presence of wind disturbance and so being a suitable method for providing additional airspeed sensor system redundancy. This paper provides one possible solution for this problem. In case of an airplane the system dynamics and so the system structure is dependent on the airspeed. The wind disturbance further complicates the problem, since it means an unknown disturbance which has a large impact on the airspeed. The MMAE method applied to state and unknown input observers is a suitable tool to overcome these difficulties as it is presented in Section 5.

The structure of the paper is as follows. In Section 2 an overview about the Multiple Model Adaptive Estimation theory is given, and in Section 3 this theory is broadened to deal with systems which have unknown inputs. An airspeed estimator algorithm based on the broadend MMAE technique is presented in Section 4. The linear and nonlinear simulation test results without and with measurement noise are discussed in Section 5. Conclusions are summarized in Section 6.

2. MULTIPLE MODEL ADAPTIVE ESTIMATION

The purpose of this section is to provide a brief overview of the state estimator MMAE method. For more information concerning the technique the reader is invited to consult with Hassani et al. (2009a) and Hassani et al. (2009b) where the authors provide a more detailed overview of the topic. Consider a plant G(t) which parameters vary with the change of the uncertain parameter κ, and we are interested in the unknown states of the plant denoted by x(t). In case the plant dynamics are known in terms of known input (u(t)) and output (y(t))

Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2016.09.014

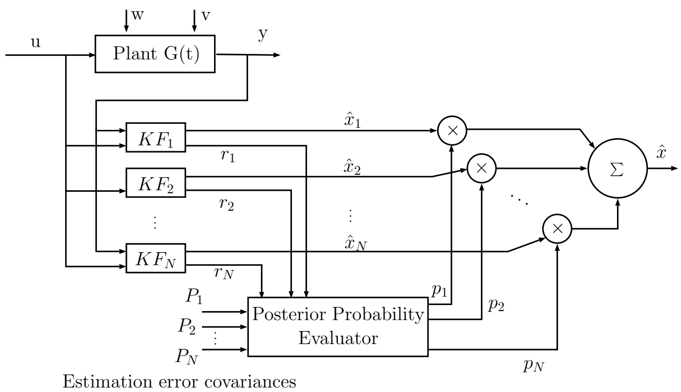

Fig. 1. The MMAE architecture

for a given κ value, than it is possible to create LTI models of the plant for distinct values of κ. This modelling approach inherently covers uncertain systems if κ is sampled from the whole possible (uncertain) parameter range and LTI models are obtained accordingly. By creating N separate LTI models at N distinct κ values, it is possible to cover a given range of the system dynamics with LTI models. By designing state observers for these models it is possible to estimate the states of the plant and the actual κ parameter value on the covered κ range. Figure 1 shows the structure of the MMAE architecture.

The parameter dependent Multiple-Input-Multiple-Output LTI system models can be characterized by the following equations:

$$\begin{aligned} x_i(t+1) &= A_i x_i(t) + B_i u(t) + W_i w(t) \\ y_i(t) &= C_i x_i(t) + D_i u(t) + V_i v(t) \end{aligned} \tag{1}$$

where $x_i(t) \in \mathbb{R}^n$ denotes the state of the system, $u(t) \in \mathbb{R}^m$ its control input, $y_i(t) \in \mathbb{R}^p$ its measured noisy output, $w(t) \in \mathbb{R}^r$ is the state noise, and $v(t) \in \mathbb{R}^q$ is the measurement noise. Vectors $w(t)$ and $v(t)$ are zero-mean white Gaussian sequences, mutually uncorrelated with covariances $E\left[w(t); w(\tau)\right] = Q_{t\tau}$ and $E\left[v(t); v(\tau)\right] = R_{t\tau}$. The initial condition $x(0)$ of (1) is Gaussian random vector with mean and covariance given by $E\left\{x_i(0)\right\} = x_{i_0}$ and $E\left\{x_i(0)x_i^T(0)\right\} = P_i(0)$. Matrices A_i, B_i, W_i, C_i, D_i, and V_i depend on the unknown parameters (κ_i) indexed by i. $W_i = I$ and $V_i = I$ can be assumed in several cases. t and $t+1$ denote consecutive discrete time steps.

The steady state Kalman Filter (KF) equations of (1) for state estimation can be written as follows

$$\begin{aligned} &\bar{x}_i(t+1) = A_i \hat{x}_i(t) + B_i u(t) \\ &\hat{x}_i(t+1) = \bar{x}_i(t+1) + L\big[y(t+1) - C_i \bar{x}_i(t+1) - \\ &\quad - D_i u(t+1)\big] \end{aligned} \tag{2}$$

Each state observer provide a state estimate $\hat{x}_i(t)$ where i=1...N. As Figure 1 shows the final state estimate ($\hat{x}(t)$) is given by (3), as the weighted sum of the $\hat{x}_i(t)$ estimates provided by the observers.

$$\hat{x}(t) = \sum_{i=1}^{N} p_i(t) \hat{x}_i(t) \tag{3}$$

The $p_i(t)$ i=1...N weights are calculated inside the Posterior Probability Evaluator (PPE) block. As Figure 1 shows this block receives the output residuals $r_i(t)$ i=1...N ($r_i(t) = y(t+1) - \hat{y}_i(t+1|t)$), where $\hat{y}_i(t+1|t) = C_i \bar{x}_i(t+1)$, and the residual covariances $\hat{P}_i$ from every filter. In Hassani et al. (2009a) the dynamic weights are calculated by the recursive formula:

$$p_i(t+1) = \frac{\beta_i e^{-E_i(t+1)}}{\sum\limits_{j=1}^{N} p_j(t) \beta_j e^{-E_j(t+1)}} p_i(t) \tag{4}$$

where $p_i(t)$ are the a-priori model probabilities (initialized as $p_i(0) = 1/N$) and $E_i(t)$ and β_i are defined as

$$\begin{aligned} &E_i(t+1) = \\ &= \left[y(t+1) - \hat{y}_i(t+1|t)\right]^T \hat{P}_i^{-1} \underbrace{\left[y(t+1) - \hat{y}_i(t+1|t)\right]}_{r_i} = \\ &= r_i(t+1)^T \hat{P}_i^{-1} r_i(t+1) \end{aligned} \tag{5}$$

$$\beta_i = \frac{1}{(2\pi)^{\frac{p}{2}} \sqrt{|\hat{P}_i|}} \tag{6}$$

where p is the dimension of $y(t)$ and $\hat{P}_i$ is the steady state covariance matrix of residuals in i^{th} KF given by

$$\hat{P}_i = C_i P_i C_i^T + R_i \tag{7}$$

here P_i is the steady state estimation error covariance matrix of the i^{th} KF obtained from the related Riccati equation. PPE requires the residuals r_i calculated from the actual measured system output $y(t+1)$ and the a priori output estimate $\hat{y}(t+1|t)$. They are scaled by the inverse of their steady state covariance matrix (see Hassani et al. (2009a)). $\beta_i e^{-E_i(t+1)}$ gives a multivariable Gaussian probability density function. In Hassani et al. (2009a) the authors prove that the p_i conditional probability of the observer which's κ_i parameter is closest to the plant's actual κ parameter will converge to 1, while the other observer's p_i probability will converge to 0. An interpolation method for smoothed parameter estimation considering the quadratic nature of E_i is published in Baar et al. (2016).

3. MMAE ALGORITHM WITH STATE AND UNKNOWN INPUT ESTIMATION

In the preceding a brief overview was given about the MMAE technique. This Section presents the modification of MMAE for state and unknown input estimation. The deterministic unknown inputs are collected to a d vector. The system equations can be written as follows

$$\begin{aligned} x_i(t+1) &= A_i x_i(t) + B_i u(t) + G_i d_i(t) + W_i w(t) \\ y_i(t) &= C_i x_i(t) + D_i u(t) + H_i d_i(t) + V_i v(t) \end{aligned} \tag{8}$$

The authors in Gillijns and Moor (2007a) and Gillijns and Moor (2007b) present an unbiased minimum-variance input and state estimator for LTI systems. The simple KFs in the MMAE architecture were replaced by these input and state estimator KFs. This way the r_i residuals generated by the filters are again able to characterize the estimation errors as in the original MMAE algorithm. This ensures that the estimation of the unknown inputs and the system states can be done at every