

Framework for state and unknown input estimation of linear time-varying systems

Lu, Peng; van Kampen, Erik-Jan; de Visser, Coen; Chu, Qiping

DOI

[10.1016/j.automat.2016.07.009](https://doi.org/10.1016/j.automat.2016.07.009)

Publication date

2016

Document Version

Accepted author manuscript

Published in

Automatica

Citation (APA)

Lu, P., van Kampen, E.-J., de Visser, C., & Chu, Q. (2016). Framework for state and unknown input estimation of linear time-varying systems. *Automatica*, *73*, 145-154.
<https://doi.org/10.1016/j.automat.2016.07.009>

Important note

To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.

Framework for state and unknown input estimation of linear time-varying systems [★]

Peng Lu ^a, Erik-Jan van Kampen ^a, Cornelis C. de Visser ^a, Qiping Chu ^a

^a*Delft University of Technology, Kluyverweg 1, 2629HS Delft, The Netherlands*

Abstract

The design of unknown-input decoupled observers and filters requires the assumption of an existence condition in the literature. This paper addresses an unknown input filtering problem where the existence condition is not satisfied. Instead of designing a traditional unknown input decoupled filter, a Double-Model Adaptive Estimation approach is extended to solve the unknown input filtering problem. It is proved that the state and the unknown inputs can be estimated and decoupled using the extended Double-Model Adaptive Estimation approach without satisfying the existence condition. Numerical examples are presented in which the performance of the proposed approach is compared to methods from literature.

Key words: Kalman filtering; state estimation; unknown input filtering; fault estimation; Double-Model Adaptive Estimation.

1 Introduction

Faults and model uncertainties such as disturbances can be represented as unknown inputs. The problem of filtering in the presence of unknown inputs has received intensive attention in the past three decades.

It is common to treat the unknown inputs as part of the system state and then estimate the unknown inputs as well as the system state [18]. This is an augmented Kalman filter, whose computational load may become excessive when the number of the unknown inputs is comparable to the states of the original system [10]. Friedland [10] derived a two-stage Kalman filter which decomposes the augmented filter into two reduced-order filters. However, Friedland's approach is only optimal in the presence of a constant bias [18]. Hsieh and Chen derived an optimal two-stage Kalman filter which performance is also optimal for the case of a random bias [18].

On the other hand, unknown input filtering can be achieved by making use of unbiased minimum-variance

estimation [16,21,5,14,15,3]. Kitanidis [21] first developed an unbiased recursive filter based on the assumption that no prior information about the unknown input is available [12]. Hou and Patton [14] used an unknown-input decoupling technique and the innovation filtering technique to derive a general form of unknown-input decoupled filters [14,15]. Darouach, Zasadzinski and Boutayeb [7] extended Kitanidis' method using a parameterizing technique to derive an optimal estimator filter. The problem of joint input and state estimation, when the unknown inputs only appear in the system equation, was addressed by Hsieh [15] and Gillijns and De Moor [11]. Gillijns and De Moor [12] further proposed a recursive three-step filter for the case when the unknown inputs also appear in the measurement equation. However, their approach requires the assumption that the distribution matrix of the unknown inputs in the measurement equation is of full rank. Cheng et al. [4] proposed a global optimal filter which removed this assumption, but this filter is limited to state estimation [1]. Later, Hsieh [17] presented a unified approach to design a specific globally optimal state estimator which is based on the desired form of the distribution matrix of the unknown input in the measurement equation [17].

However, all the above-mentioned filters require the assumption that an existence condition is satisfied. This necessary condition is given by Hou and Patton [14] and Darouach, Zasadzinski and Boutayeb [7], in the form of rank condition (5). Hsieh [17] presents different decoupling approaches for different special cases. However,

[★] This paper was not presented at any IFAC meeting. Corresponding author Peng Lu. Tel. +31 152783466. Fax +31 152786480.

Email addresses: P.Lu-1@tudelft.nl (Peng Lu), E.vanKampen@tudelft.nl (Erik-Jan van Kampen), c.c.devisser@tudelft.nl (Cornelis C. de Visser), q.p.chu@tudelft.nl (Qiping Chu).

these approaches also have to satisfy the existence condition (5). In some applications, such as that presented in the current paper, the existence condition is not satisfied. Therefore, a traditional unknown input decoupled filter can not be designed.

Recently, particle filters are also applied to unknown input estimation [13,8,28]. These filters can cope with systems with non-Gaussian noise and have a number of applications such as for robot fault detection [2,9,30]. In this paper, the performance of unknown input estimation using particle filters will be compared with that of our approach.

This paper proposes an extended Double-Model Adaptive Estimation (DMAE) approach, which can cope with the unknown input filtering problem when a traditional unknown input filter can not be designed. The original DMAE approach, which was proposed by Lu et al. [22] for the estimation of unknown inputs in the measurement equation, is extended to allow estimation of the unknown inputs which appear both in the system equation and the measurement equation. The unknown inputs are augmented as system states and are modeled as random walk processes. The unknown inputs in the system equation are assumed to be Gaussian random processes of which covariances are estimated on-line. It is proved that the state and unknown inputs can be estimated and decoupled while not requiring the existence condition. Two illustrative examples are given to demonstrate the effectiveness of the proposed approach with comparison to other methods from literature such as the Robust Three-Step Kalman Filter (RTSKF) [12], the Optimal Two-Stage Kalman Filter (OTSKF) [18] and the particle filters [13,8].

The structure of the paper is as follows: the preliminaries of the paper are given in Section 2, formulating the filtering problem when the existence condition for a traditional unknown input decoupled filter is not satisfied and generalizing the DMAE approach. In Section 3, the extension of the DMAE approach to the filtering problem when the unknown inputs appear both in the system equation and the measurement equation is presented. Furthermore, the on-line estimation of the covariance matrix of the unknown inputs is introduced. It is proved that the state and the unknown inputs can still be estimated and decoupled in Section 4. In Section 5, two illustrative examples are given to show the performance of the proposed approach with comparison to some existing unknown-input decoupled filters. Finally, Section 6 concludes the paper.

2 The DMAE approach

This section presents the problem formulation and the DMAE approach.

2.1 Problem formulation

Consider the following linear time-varying system:

$$x_{k+1} = A_k x_k + B_k u_k + E_k d_k + w_k \quad (1)$$

$$y_k = H_k x_k + F_k f_k + v_k \quad (2)$$

where $x_k \in \mathbb{R}^n$ represents the system states, $y_k \in \mathbb{R}^m$ the measurements, d_k and f_k are the unknown inputs. Specifically, $d_k \in \mathbb{R}^{n_d}$ the disturbances, $f_k \in \mathbb{R}^{n_f}$ are the output faults. w_k and v_k are assumed to be uncorrelated zero-mean white noise sequences with covariance Q_k and R_k respectively. u_k , the known inputs, is omitted in the following discussion because it does not affect the filter design [14]. Without loss of generality, we consider the case: $n = m = n_d = n_f$ and $\text{rank } H_k = \text{rank } E_k = \text{rank } F_k = m$, which implies all the states are influenced by d_k and f_k . It should be noted that the approach proposed in this paper can be readily extended to the case when $n \neq m$ or $\text{rank } H_k \neq \text{rank } E_k$.

The unknown inputs are denoted as d'_k , i.e., $d'_k = \begin{bmatrix} d_k \\ f_k \end{bmatrix} \in \mathbb{R}^{n_{d'}}$. Then, model (1) and (2) can be reformulated into the general form as given in Hou and Patton [14] and Darouach, Zasadzinski and Boutayeb [7]:

$$x_{k+1} = A_k x_k + E'_k d'_k + w_k \quad (3)$$

$$y_k = H_k x_k + F'_k d'_k + v_k \quad (4)$$

In this paper, $E'_k = [E_k \ 0]$, $F'_k = [0 \ F_k]$. The existence of an unknown-input decoupled filter must satisfy the following existence condition [14,7]:

$$\text{rank} \begin{bmatrix} F'_k & H_k E'_k \\ 0 & F'_k \end{bmatrix} = \text{rank} [F'_k] + \text{rank} \begin{bmatrix} E'_k \\ F'_k \end{bmatrix} \quad (5)$$

In our case, since $\text{rank } H_k = m$, the left-hand side of condition (5) is $2m$ while the right-hand side is $3m$. Therefore, the above existence condition does not hold, which means that all the unknown-input filters mentioned in the introduction can not be directly implemented.

In this paper, we consider the consecutive bias fault estimation of a system subjected to disturbances, as described in Eqs. (1) and (2). Although the existence condition of designing a traditional unknown input decoupled filter is not satisfied, it will be shown that the unknown inputs can still be decoupled using an extended DMAE approach.

Remark 1. The model described by Eqs. (1) and (2) is useful for applications where the disturbances appear in the system equation and the faults appear in the measurement equation, such as bias fault estimation in aircraft air data sensors [22].

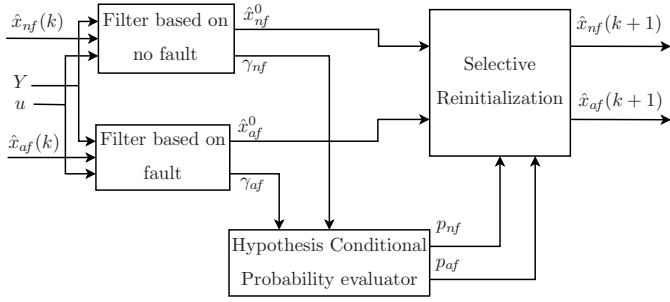


Fig. 1. Block diagram for the DMAE approach

2.2 The DMAE approach

The DMAE1 approach proposed in Lu et al. [22] considers the model (1) and (2) for $d_k = 0$ ($n_d = 0$). It is referred to as the DMAE approach in this paper, which is generalized in the following.

The DMAE [22], which is a modified approach of multiple-model-based approach [23,24], is composed of two Kalman Filters (KFs) operating in parallel: a no-fault (or fault-free) filter and an augmented fault filter. These two filters are based on two modes of the system: fault-free ($f_k = 0$) and faulty ($f_k \neq 0$). The two filters use the same vector of measurements Y and vector of input u , and are based on the same equations of motion, while each hypothesizes a different fault scenario. The state vector of the no-fault filter x_{nf} and that of the augmented fault filter x_{af} are as follows:

$$x_{nf,k} = x_k, \quad x_{af,k} = \begin{bmatrix} x_{nf,k} \\ f_k \end{bmatrix} \quad (6)$$

where “ nf ” means no fault and “ af ” means augmented fault. It can be noted that the state vector of the augmented fault filter is the state vector of the no-fault filter with augmentation of the fault vector f_k .

At time step k , each of the filters produces a state estimate $\hat{x}_i^0(k)$ and a vector of innovations $\gamma_i(k)$. The principle is that the KF which produces the most well-behaved innovations, contains the model which matches the true faulty model best [23,24]. The block diagram of the DMAE is given in Fig. 1.

A hypothesis test uses the innovation $\gamma_i(k)$ and the innovation covariance matrix $C_i(k)$ of the filters in order to assign a conditional probability to each of the filters. Let a denote the fault scenarios of the system. If we define the hypothesis conditional probability $p_i(k)$ as the probability that a is assigned a_i for $i = 1, 2$ ($a_1 = nf$, $a_2 = af$), conditioned on the measurement history up to time step k :

$$p_i(k) = \Pr[a = a_i | Y(k) = Y_k], \quad i = 1, 2 \quad (7)$$

then the conditional probability of the two filters can be updated recursively using the following equation:

$$p_i(k) = \frac{f_{y_k|a, Y_{k-1}}(y_k | a_i, Y_{k-1}) p_i(k-1)}{\sum_{j=1}^2 f_{y_k|a, Y_{k-1}}(y_k | a_j, Y_{k-1}) p_j(k-1)}, \quad i = 1, 2 \quad (8)$$

where Y_{k-1} is the measurement history vector which is defined as $Y_{k-1} = \{y(1), y(2), \dots, y(k-1)\}$.

$f_{y_k|a, Y_{k-1}}(y_k | a_i, Y_{k-1})$ is the probability density function which is given by the following Gaussian form [24]:

$$f_{y(k)|a, Y_{k-1}}(y(k) | a_i, Y_{k-1}) = \beta_i(k) \exp\{-\gamma_i^T(k) C_i^{-1}(k) \gamma_i(k) / 2\} \quad (9)$$

where

$$\beta_i(k) = \frac{1}{(2\pi)^{m/2} |C_i(k)|^{1/2}} \quad (10)$$

In Eq. (10), $|\bullet|$ denotes the determinant of the covariance matrix $C_i(k)$ which is computed by the KF at time step k . The filter which matches the fault scenario produces the smallest innovation which is the difference between the estimated measurement and the true measurement. Therefore, the conditional probability of the filter which matches the true fault scenario is the highest between the two filters. After the computation of the conditional probability, the state estimate of the nonlinear system $\hat{x}(k)$ can be generated by the weighted state estimate $\hat{x}_i(k)$ of the two filters:

$$\hat{x}(k) = \sum_{i=1}^2 \hat{x}_i(k) p_i(k) = \hat{x}_{nf}(k) p_{nf}(k) + \hat{x}_{af}(k) p_{af}(k). \quad (11)$$

The fault is only estimated by the augmented fault filter and the estimate is denoted as $\hat{f}(k)$. The probability-weighted fault estimate of the DMAE approach $\bar{f}(k)$ is calculated as follows:

$$\bar{f}(k) = \hat{f}(k) p_{af}(k) \quad (12)$$

The core of the DMAE approach is selective reinitialization. The flow chart of the selective reinitialization algorithm is presented in Fig. 2.

In the algorithm, \hat{x}_{nf}^0 (\hat{x}_{af}^0) and \hat{x}_{nf} (\hat{x}_{af}) denote the state estimate of the no-fault (augmented fault) filter before and after the reinitialization, respectively. P_{nf}^0 (P_{af}^0) and P_{nf} (P_{af}) denote the covariance of state estimate error of the no-fault (augmented fault) filter before and after the reinitialization, respectively. \hat{x}_t , p_t and P_t are the vectors which contain the state estimate, model probability and the covariance matrix of state estimation error of the no-fault filter and the fault filter respectively. $i_{max,k}$ is the index of the model with the maximum model probability

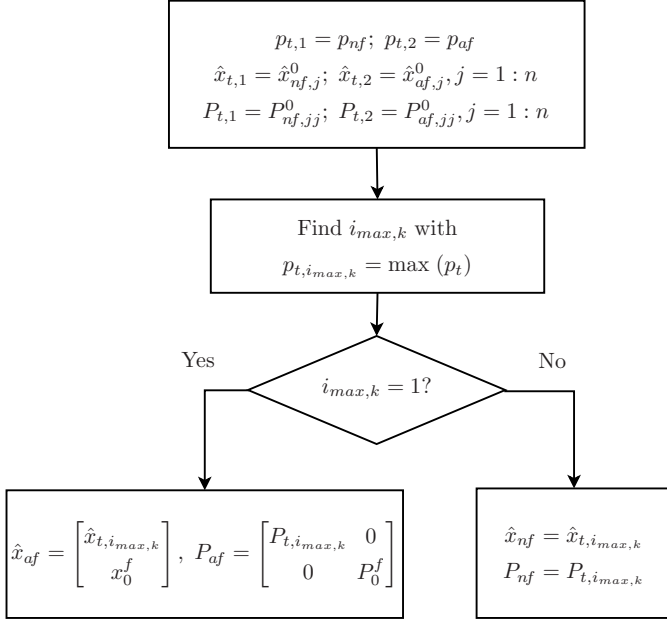


Fig. 2. Flow chart of the Selective Reinitialization algorithm. Note n refers to the dimension of \hat{x}_{nf} .

at time step k . x_0^f and P_0^f are the parameters which are used for the initialization of the fault filter.

3 Extension of the DMAE approach

The DMAE approach can achieve an unbiased estimation of x_k and f_k when $d_k = 0$ [22]. However, when $d_k \neq 0$, the unknown-input filtering problem becomes more challenging. Since the existence condition (5) is no longer satisfied, traditional unknown-input decoupled filters can not be designed.

In this section, the DMAE is extended to the case when $d_k \neq 0$. In order to achieve this, the state vectors of the no-fault filter and augmented fault filter are changed to:

$$\bar{x}_{nf,k} = \begin{bmatrix} x_k \\ d_k \end{bmatrix}, \bar{x}_{af,k} = \begin{bmatrix} \bar{x}_{nf,k} \\ f_k \end{bmatrix} \quad (13)$$

where $\bar{x}_{nf,k} \in \mathbb{R}^{n+n_d}$ and $\bar{x}_{af,k} \in \mathbb{R}^{n+n_d+n_f}$. The state vector of the augmented fault filter is that of the no-fault filter augmented with the fault vector. Therefore, the state vector of the no-fault filter can be inferred from that of the augmented fault filter and vice versa.

The random walk process provides a useful and general tool for the modeling of unknown time-varying processes [10,27,15]. d_k can be modeled by a random walk process [27,15] as:

$$d_{k+1} = d_k + w_{d,k}, \quad (14)$$

where $w_{d,k}$ is a white noise sequence with covariance: $E\{w_{d,k}(w_{d,l})^T\} = Q_k^d \delta_{kl}$. f_k is also modeled as a random walk process as:

$$f_{k+1} = f_k + w_{f,k}, \quad (15)$$

where $w_{f,k}$ is a white noise sequence with covariance: $E\{w_{f,k}(w_{f,l})^T\} = Q_k^f \delta_{kl}$. Then, the system model and measurement model of the no-fault filter can be described as follows:

$$\bar{x}_{nf,k+1} = \bar{A}_{nf,k} \bar{x}_{nf,k} + \bar{w}_{nf,k} \quad (16)$$

$$y_k = \bar{H}_{nf,k} \bar{x}_{nf,k} + v_k \quad (17)$$

where

$$\bar{A}_{nf,k} = \begin{bmatrix} A_k & E_k \\ 0 & I \end{bmatrix}, \bar{H}_{nf,k} = [H_k \ 0], \bar{w}_{nf,k} = \begin{bmatrix} w_k \\ w_{d,k} \end{bmatrix} \quad (18)$$

The model of the augmented fault filter is as follows:

$$\bar{x}_{af,k+1} = \bar{A}_{af,k} \bar{x}_{af,k} + \bar{w}_{af,k} \quad (19)$$

$$y_k = \bar{H}_{af,k} \bar{x}_{af,k} + v_k \quad (20)$$

where

$$\bar{A}_{af,k} = \begin{bmatrix} \bar{A}_{nf,k} & 0 \\ 0 & I \end{bmatrix}, \bar{H}_{af,k} = [\bar{H}_{nf,k} \ F_k], \bar{w}_{af,k} = \begin{bmatrix} \bar{w}_{nf,k} \\ w_{f,k} \end{bmatrix} \quad (21)$$

Since the difference from the DMAE in Lu et al. [22] is the augmentation of d_k , only the covariance related to $w_{d,k}$, i.e., Q_k^d is discussed below. It should be noted that Q_k^d is usually unknown, the optimality of the filter can be compromised by a poor choice of Q_k^d [21,15]. If Q_k^d is not properly chosen, it can influence the estimation of d_k as well as x_k .

This paper proposes a method to adapt Q_k^d by making use of the augmented fault filter of the DMAE approach. To compensate for the effect of a bad choice of Q_k^d on the estimation of x_k , the system noise vector $\bar{w}_{nf,k}$ in Eqs.(16), (18) and (21) is modified to:

$$\bar{w}_{nf,k} = \begin{bmatrix} w_k + w'_k \\ w_{d,k} \end{bmatrix} \quad (22)$$

where w'_k is the noise used to compensate for the effect of a bad choice of Q_k^d on the estimation of x_k . In this paper, we approximate w'_k by $E_k w_{d,k}$. Therefore, $\bar{w}_{nf,k}$ is

$$\bar{w}_{nf,k} = \begin{bmatrix} w_k + E_k w_{d,k} \\ w_{d,k} \end{bmatrix} \quad (23)$$

Let $\hat{x}_{af,k-1|k-1}$ denote the unbiased estimate of $\bar{x}_{af,k-1}$ given measurements up to time $k-1$. $\hat{x}_{k-1|k-1}$, $\hat{d}_{k-1|k-1}$ and $\hat{f}_{k-1|k-1}$ denote the estimates of x_{k-1} , d_{k-1} and f_{k-1} , respectively. The innovation of the augmented fault filter is:

$$\begin{aligned}\gamma_{af,k} &= y_k - \bar{H}_{af,k} \hat{x}_{af,k|k-1} \\ &= H_k A_{k-1} \tilde{x}_{k-1|k-1} + H_k E_{k-1} \tilde{d}_{k-1|k-1} + F_k \tilde{f}_{k-1|k-1} \\ &\quad + H_k w_{k-1} + H_k E_{k-1} w_{d,k-1} + F_k w_{f,k-1} + v_k\end{aligned}\quad (24)$$

with

$$\tilde{x}_{k-1|k-1} := x_{k-1} - \hat{x}_{k-1|k-1} \quad (25)$$

$$\tilde{d}_{k-1|k-1} := d_{k-1} - \hat{d}_{k-1|k-1} \quad (26)$$

$$\tilde{f}_{k-1|k-1} := f_{k-1} - \hat{f}_{k-1|k-1} \quad (27)$$

Therefore, the innovation covariance of the augmented fault filter is:

$$\begin{aligned}C_{af,k} &= E\{\gamma_{af,k} \gamma_{af,k}^T\} \\ &= H_k A_{k-1} P_{k-1|k-1}^x A_{k-1}^T H_k^T \\ &\quad + H_k E_{k-1} P_{k-1|k-1}^d E_{k-1}^T H_k^T + F_k P_{k-1|k-1}^f F_k^T \\ &\quad + H_k A_{k-1} P_{k-1|k-1}^{xd} E_{k-1}^T H_k^T + H_k A_{k-1} P_{k-1|k-1}^{xf} F_k^T \\ &\quad + H_k E_{k-1} P_{k-1|k-1}^{dx} A_{k-1}^T H_k^T + H_k E_{k-1} P_{k-1|k-1}^{df} F_k^T \\ &\quad + F_{k-1} P_{k-1|k-1}^{fx} A_{k-1}^T H_k^T + F_k P_{k-1|k-1}^{fd} E_{k-1}^T H_k^T + R_k \\ &\quad + H_k Q_{k-1} H_k^T + H_k E_{k-1} Q_{k-1}^d E_{k-1}^T H_k^T + F_k Q_k^f F_k^T\end{aligned}\quad (28)$$

where the covariance matrices are defined as follows:

$$\begin{aligned}P_{k|k}^x &:= E[\tilde{x}_{k|k} \tilde{x}_{k|k}^T], \quad P_{k|k}^d := E[\tilde{d}_{k|k} \tilde{d}_{k|k}^T] \\ P_{k|k}^f &:= E[\tilde{f}_{k|k} \tilde{f}_{k|k}^T], \quad P_{k|k}^{xd} := E[\tilde{x}_{k|k} \tilde{d}_{k|k}^T] \\ P_{k|k}^{dx} &:= E[\tilde{d}_{k|k} \tilde{x}_{k|k}^T], \quad P_{k|k}^{xf} := E[\tilde{x}_{k|k} \tilde{f}_{k|k}^T] \\ P_{k|k}^{fx} &:= E[\tilde{f}_{k|k} \tilde{x}_{k|k}^T], \quad P_{k|k}^{df} := E[\tilde{d}_{k|k} \tilde{f}_{k|k}^T] \\ P_{k|k}^{fd} &:= E[\tilde{f}_{k|k} \tilde{d}_{k|k}^T].\end{aligned}$$

The actual $C_{af,k}$ is approximated as follows [26,29]:

$$\hat{C}_{af,k} = \frac{1}{N} \sum_{j=k-N+1}^k \gamma_{af,j} \gamma_{af,j}^T \quad (29)$$

Q_k^d can be approximated by the main diagonal of

$$E_{k-1}^{-1} H_k^{-1} \tilde{Q}_k (H_k^T)^{-1} (E_{k-1}^T)^{-1} \quad (30)$$

with \tilde{Q}_k is a diagonal matrix defined as:

$$\tilde{Q}_k := \text{diag}(\max\{0, \hat{Q}_{k,11}\}, \dots, \max\{0, \hat{Q}_{k,mm}\}) \quad (31)$$

where $\hat{Q}_{k,jj}$, $j = 1, 2, \dots, m$ is the j th diagonal element of \hat{Q}_k which is denoted as:

$$\hat{Q}_k = (\hat{C}_{af,k} - H_k Q_{k-1} H_k^T - F_k Q_k^f F_k^T - R_k) \quad (32)$$

The restriction $\tilde{Q}_{k,jj} \geq 0$, $j = 1, 2, \dots, m$ in Eq. (31) is to preserve the properties of a variance [19].

4 Unknown input decoupled filtering

This section proves that the unknown input decoupled filtering can be achieved using the extended DMAE approach which does not need to satisfy the existence condition (5). Let l ($l \geq 1$) denote the time step when the first fault occurs and l_e denote the time step when the first fault is removed, which means $f_k = 0$ when $k < l$ and $f_k \neq 0$ when $l \leq k \leq l_e$. Without loss of generality, it will be proven that f_k can be estimated when $k \leq l_e$.

4.1 Unknown input estimation during $k < l$

Theorem 1 During $k < l$, an unbiased estimate of d_k can be achieved by the fault-free filter of the extended DMAE approach.

PROOF. When $k < l$, $f_k = 0$. The fault-free model matches the true fault scenario while the augmented fault filter does not. Therefore, according to the DMAE approach, $i_{max,k} = 1$ during this time period.

The system model during this period is as follows:

$$x_{k+1} = A_k x_k + E_k d_k + w_k \quad (33)$$

$$y_k = H_k x_k + v_k \quad (34)$$

Under this situation, d_k can be estimated using the fault-free filter whose convergence condition will be discussed later. \square

The estimation of d_k and f_k when $l \leq k \leq l_e$ will be discussed in the following.

4.2 Unknown input estimation at $k = l$

For the sake of readability, the subscript “af” will be discarded for the remainder of the section. All the variables with a bar on top in the remainder of this section refer to the augmented fault filter.

Using the DMAE approach, the Kalman gain \bar{K}_l can be partitioned as follows:

$$\bar{K}_l = \begin{bmatrix} K_l^x \\ K_l^d \\ K_l^f \end{bmatrix} \quad (35)$$

where K_l^x , K_l^d and K_l^f are the Kalman gains associated with x_k , d_k and f_k , respectively.

Lemma 2 *Let $\hat{x}_{l-1|l-1}$ and $\hat{d}_{l-1|l-1}$ be unbiased, if x_0^f is chosen to be 0 or sufficiently small, then f_l can be estimated by the augmented fault filter if and only if K_l^f satisfies*

$$K_l^f F_l = I. \quad (36)$$

PROOF. The innovation of the augmented filter is

$$\bar{\gamma}_l = e_l + F_l f_l \quad (37)$$

where e_l is defined as

$$e_l := H_l A_{l-1} \tilde{x}_{l-1|l-1} + H_l E_{l-1} \tilde{d}_{l-1|l-1} + H_l w_{l-1} + H_l E_{l-1} w_{d,l-1} + v_l \quad (38)$$

Since $\hat{x}_{l-1|l-1}$ and $\hat{d}_{l-1|l-1}$ are unbiased (this can be achieved by the DMAE1 in Lu et. al [22] since $f_k = 0$ when $k < l$), $E[e_l] = 0$.

Consequently, the expectation of $\bar{\gamma}_l$ is:

$$E[\bar{\gamma}_l] = F_l f_l. \quad (39)$$

The estimation of the fault can be given by

$$\begin{aligned} \hat{f}_{l|l} &= \hat{f}_{l|l-1} + K_l^f \bar{\gamma}_l \\ &= \hat{f}_{l-1|l-1} + K_l^f \bar{\gamma}_l \end{aligned} \quad (40)$$

Since $i_{max,k} = 1$ when $k < l$, according to the flow chart of the selective reinitialization algorithm given in Fig. 2, Eq. (40) can be further written into

$$\hat{f}_{l|l} = x_0^f + K_l^f \bar{\gamma}_l \quad (41)$$

Substituting (37) into (41), yields

$$\hat{f}_{l|l} = K_l^f F_l f_l + K_l^f e_l \quad (42)$$

Consequently, the expectation of $\hat{f}_{l|l}$

$$E[\hat{f}_{l|l}] = E[K_l^f F_l f_l]. \quad (43)$$

Therefore, it can be concluded that f_l can be estimated if and only if K_l^f satisfies

$$K_l^f F_l = I. \quad \square \quad (44)$$

Theorem 3 *Let $\hat{x}_{l-1|l-1}$ and $\hat{d}_{l-1|l-1}$ be unbiased, then f_l can be estimated by the augmented fault filter of the DMAE approach by choosing a sufficiently large P_0^f and a sufficiently small x_0^f .*

PROOF. Define the following covariance matrix:

$$\bar{P}_{l-1|l-1} := E[\tilde{x}_{l-1|l-1} \tilde{x}_{l-1|l-1}^T]$$

where $\tilde{x}_{l-1|l-1} = \bar{x}_{l-1} - \hat{x}_{l-1|l-1}$.

Due to the selective reinitialization algorithm given in Fig. 2, $P_{l-1|l-1}^f = P_0^f$. Therefore, the covariance of the state prediction error $\bar{P}_{l|l-1}$ can be computed and partitioned as follows:

$$\begin{aligned} \bar{P}_{l|l-1} &= \bar{A}_{l-1} \begin{bmatrix} P_{l-1|l-1}^x & P_{l-1|l-1}^{xd} & 0 \\ P_{l-1|l-1}^{dx} & P_{l-1|l-1}^d & 0 \\ 0 & 0 & P_0^f \end{bmatrix} \bar{A}_{l-1}^T \\ &+ \begin{bmatrix} Q_{l-1} + E_{l-1} Q_{l-1}^d E_{l-1}^T & E_{l-1} Q_{l-1}^d & 0 \\ Q_{l-1}^d E_{l-1}^T & Q_{l-1}^d & 0 \\ 0 & 0 & Q_{l-1}^f \end{bmatrix} \end{aligned} \quad (45)$$

$$= \begin{bmatrix} P_{l|l-1}^x & P_{l|l-1}^{xd} & 0 \\ P_{l|l-1}^{dx} & P_{l|l-1}^d & 0 \\ 0 & 0 & P_{l|l-1}^f \end{bmatrix} \quad (46)$$

where

$$\begin{aligned} P_{l|l-1}^x &:= A_{l-1} P_{l-1|l-1}^x A_{l-1}^T + E_{l-1} P_{l-1|l-1}^d E_{l-1}^T \\ &+ A_{l-1} P_{l-1|l-1}^{xd} E_{l-1}^T + E_{l-1} P_{l-1|l-1}^{dx} A_{l-1}^T \\ &+ Q_{l-1} + E_{l-1} Q_{l-1}^d E_{l-1}^T \\ P_{l|l-1}^d &:= P_{l-1|l-1}^d + Q_{l-1}^d \\ P_{l|l-1}^{xd} &:= A_{l-1} P_{l-1|l-1}^{xd} + E_{l-1} P_{l-1|l-1}^d + E_{l-1} Q_{l-1}^d \\ P_{l|l-1}^{dx} &:= P_{l-1|l-1}^{dx} A_{l-1}^T + P_{l-1|l-1}^d E_{l-1}^T + Q_{l-1}^d E_{l-1}^T \\ P_{l|l-1}^f &:= P_0^f + Q_{l-1}^f \end{aligned}$$

Define

$$\bar{C}_l := \bar{H}_l \bar{P}_{l|l-1} \bar{H}_l^T + R_l. \quad (47)$$

Substituting Eqs. (21) and (46) into the above equation, it follows that

$$\bar{C}_l = H_l P_{l|l-1}^x H_l^T + F_l P_{l|l-1}^f F_l^T + R_l \quad (48)$$

Consequently, the Kalman gain of the augmented filter can be calculated and partitioned as follows:

$$\begin{aligned} \bar{K}_l &= \bar{P}_{l|l-1} \bar{H}_l^T \bar{C}_l^{-1} \\ &= \begin{bmatrix} P_{l|l-1}^x H_l^T \\ P_{l|l-1}^{dx} H_l^T \\ P_{l|l-1}^f F_l^T \end{bmatrix} \bar{C}_l^{-1} \end{aligned} \quad (49)$$

If P_0^f is chosen sufficiently large, then $P_{l|l-1}^f \approx P_0^f$ and $\bar{C}_l \approx F_l P_0^f F_l^T$. It follows that

$$\bar{K}_l = \begin{bmatrix} P_{l|l-1}^x H_l^T \bar{C}_l^{-1} \\ P_{l|l-1}^{dx} H_l^T \bar{C}_l^{-1} \\ F_l^{-1} \end{bmatrix} \quad (50)$$

Therefore, $K_l^f = F_l^{-1}$. It follows from Lemma 2 that f_l can be estimated. \square

4.3 Unknown input estimation during $l < k \leq l_e$

Theorem 4 *Provided that f_k has been estimated at $k = l$, d_k can be estimated by the augmented fault filter of the extended DMAE approach.*

PROOF. During this period, the augmented fault model matches the true fault scenario. Therefore, $i_{max,k} = 2$, which means that the fault-free filter is reinitialized by the fault filter during this period. Since this paper considers bias fault, f_k is constant for $l < k \leq l_e$. Therefore, during this period, we can set:

$$\begin{aligned} \hat{x}_{k|k-1} &= \begin{bmatrix} \hat{x}_{k|k-1}^* \\ \hat{f}_{l|l} \end{bmatrix}, \bar{P}_{k|k-1} = \begin{bmatrix} P_{k|k-1}^* & 0 \\ 0 & P_{l|l}^f \end{bmatrix} \\ \hat{x}_{k|k} &= \begin{bmatrix} \hat{x}_{k|k}^* \\ \hat{f}_{l|l} \end{bmatrix}, \bar{P}_{k|k} = \begin{bmatrix} P_{k|k}^* & 0 \\ 0 & P_{l|l}^f \end{bmatrix}, \bar{K}_k = \begin{bmatrix} K_k^* \\ 0 \end{bmatrix}, \end{aligned} \quad (51)$$

where

$$\begin{aligned} \hat{x}_{k|k-1}^* &:= \begin{bmatrix} \hat{x}_{k|k-1} \\ \hat{d}_{k|k-1} \end{bmatrix}, P_{k|k-1}^* := \begin{bmatrix} P_{k|k-1}^x & P_{k|k-1}^{xd} \\ P_{k|k-1}^{dx} & P_{k|k-1}^d \end{bmatrix}, \\ \hat{x}_{k|k}^* &:= \begin{bmatrix} \hat{x}_{k|k} \\ \hat{d}_{k|k} \end{bmatrix}, P_{k|k}^* := \begin{bmatrix} P_{k|k}^x & P_{k|k}^{xd} \\ P_{k|k}^{dx} & P_{k|k}^d \end{bmatrix}, K_k^* := \begin{bmatrix} K_k^x \\ K_k^d \end{bmatrix} \end{aligned} \quad (52)$$

are updated by the normal Kalman filtering procedure. It can be seen that during this period, the estimation of the fault and the covariance are:

$$\hat{f}_{k|k} = \hat{f}_{l|l}, P_{k|k}^f = P_{l|l}^f, l < k \leq l_e \quad (53)$$

It can be inferred that the model of the fault filter is equivalent to:

$$x_{k+1} = A_k x_k + E_k d_k + w_k \quad (54)$$

$$y_k = H_k x_k + F_k \hat{f}_{l|l} + v_k \quad (55)$$

As can be seen, the only unknown input is d_k since the fault filter treats f_k as a known input during this period. Since a known input does not affect the design of a filter [14], the convergence condition of this fault filter is the same as that of the fault-free filter based on Eqs. (33) and (34).

Therefore, d_k can be estimated using the augmented fault filter under the same condition as for the model described by Eqs. (33) and (34). \square

4.4 Error analysis

In the previous sections, it is assumed that $\hat{x}_{l-1|l-1}$ and $\hat{d}_{l-1|l-1}$ are unbiased. We analyze the estimation error of f_l when $\hat{x}_{l-1|l-1}$ and $\hat{d}_{l-1|l-1}$ are biased.

Through Eq. (44), Eq. (42) can be further rewritten into

$$\hat{f}_{l|l} = f_l + F_l^{-1} e_l \quad (56)$$

Substitute Eq. (38) into Eq. (56), it follows

$$\begin{aligned} \hat{f}_{l|l} &= f_l + F_l^{-1} (H_l A_{l-1} \tilde{x}_{l-1|l-1} + H_l E_{l-1} \tilde{d}_{l-1|l-1} \\ &\quad + H_l w_{l-1} + H_l E_{l-1} w_{d,l-1} + v_l) \end{aligned} \quad (57)$$

The estimation error of f_l as a function of $\tilde{x}_{l-1|l-1}$ and $\tilde{d}_{l-1|l-1}$ can be obtained as follows:

$$\tilde{f}_{l|l} = f_l - \hat{f}_{l|l} \quad (58)$$

$$\begin{aligned} &= F_l^{-1} (H_l A_{l-1} \tilde{x}_{l-1|l-1} + H_l E_{l-1} \tilde{d}_{l-1|l-1} \\ &\quad + H_l w_{l-1} + H_l E_{l-1} w_{d,l-1} + v_l) \end{aligned} \quad (59)$$

If $\tilde{x}_{l-1|l-1}$ and $\tilde{d}_{l-1|l-1}$ are unbiased, the expectation of $\tilde{f}_{l|l}$ is zero, which means the fault estimate is unbiased. If $\tilde{x}_{l-1|l-1}$ and $\tilde{d}_{l-1|l-1}$ are biased, assume

$$aI \leq A_{l-1} \leq \bar{a}I, \quad \underline{f}I \leq F_{l-1} \leq \bar{f}I, \quad (60)$$

$$\underline{h}I \leq H_{l-1} \leq \bar{h}I, \quad eI \leq E_{l-1} \leq \bar{e}I, \quad (61)$$

$$\underline{e}_x I \leq \tilde{x}_{l-1|l-1} \leq \bar{e}_x I, \quad \underline{e}_d I \leq \tilde{d}_{l-1|l-1} \leq \bar{e}_d I, \quad (62)$$

$$\underline{w}I \leq w_{l-1} \leq \bar{w}I, \quad \underline{w}_d I \leq w_{d,l-1} \leq \bar{w}_d I, \quad (63)$$

$$\underline{v}I \leq v_{l-1} \leq \bar{v}I. \quad (64)$$

Then it follows that the fault estimation error is bounded by the following:

$$\left[\frac{\underline{h}(\underline{a}e_x + \underline{e}e_d + \underline{w} + \underline{e}w_d) + \underline{v}}{\underline{f}}, \frac{\bar{h}(\bar{a}\bar{e}_x + \bar{e}\bar{e}_d + \bar{w} + \bar{e}\bar{w}_d) + \bar{v}}{\bar{f}} \right] \quad (65)$$

4.5 Discussion

For the model given in Eqs. (33) and (34), the convergence condition for time-invariant case has been given by Darouach et al. [6], which is given as follows:

$$\text{rank} \begin{bmatrix} zI - A & -E \\ H & 0 \end{bmatrix} = n + n_d, \forall z \in \mathcal{C}, |z| \geq 1 \quad (66)$$

This convergence condition is also required by traditional unknown input filters such as those in Darouach, Zasadzinski and Boutayeb [7] and Cheng et al. [4].

The system considered in this paper is linear and the noise is assumed to be Gaussian. If the system is non-linear, the DMAE should be extended using Unscented Kalman Filters [20,22] or particle filters [13,8,28]. If the system noise is non-Gaussian, then it should be extended by making use of particle filters [13,8,28]. However, this is out of the scope of the present paper.

5 Illustrative examples with comparison to existing methods

In this section, two examples similar to that in [27], [7] and [16] are provided to demonstrate the performance of the extended DMAE approach. Note that both E and F are of full rank in this example.

The system is described by model (1) and (2) where

$$A = \begin{bmatrix} -0.0005 & -0.0084 \\ 0.0517 & 0.8069 \end{bmatrix}, B = \begin{bmatrix} 0.1815 \\ 1.7902 \end{bmatrix}, \quad (67)$$

$$E = \begin{bmatrix} 0.629 & 0 \\ 0 & -0.52504 \end{bmatrix}, H = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, F = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad (68)$$

$$Q = \begin{bmatrix} 0.002^2 & 0 \\ 0 & 0.002^2 \end{bmatrix}, R = \begin{bmatrix} 0.01^2 & 0 \\ 0 & 0.01^2 \end{bmatrix} \quad (69)$$

The input u_k is: $u_k = -0.5$ when $200 < k \leq 300$, otherwise $u_k = 0.5$. f_k is given by the red solid lines in Fig. 3(c). It can be noted that the number of unknown inputs in [27], [7] and [16] is n_d ($n_d = 2$) while this paper deals with $2n_d$ unknown inputs.

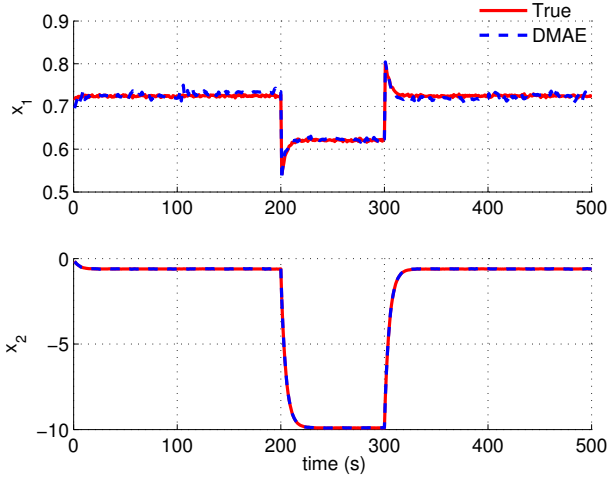
In both examples, since $E'_k = [E_k \ 0]$, $F'_k = [0 \ F_k]$, condition (5) is not satisfied. In addition, $\text{rank } y_k < \text{rank } d'_k$. Consequently, all the unknown input decoupled filters in the introduction are not applicable to solve the problem, except for special cases when $d_k = 0$ or $f_k = 0$. N in Eq. (29) is set to be 10. In both examples, $Q_k^f = 0$, Q_k^d is updated by the main diagonal of the matrix given in (30), $x_0^f = [10^{-3}, 10^{-3}]^T$, $P_0^f = 10^2 I$.

Example 1. In this example, d_k is a constant bias vector, which is shown by the red solid lines in Fig. 3(b). The condition (5) is not satisfied. Therefore, traditional unknown input filters, which require the satisfaction of condition (5), can not be implemented.

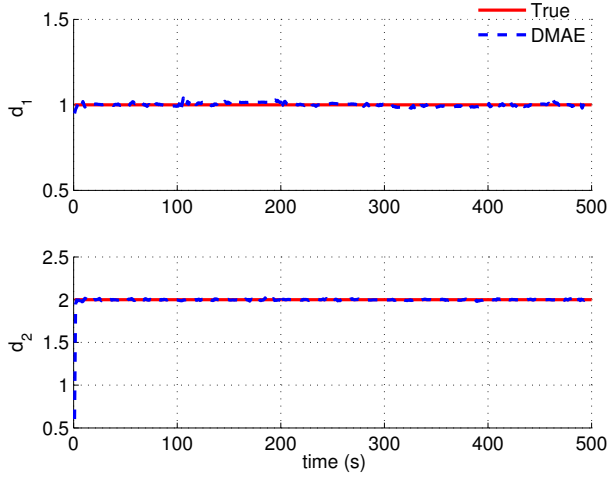
The extended DMAE approach is implemented. The true and estimated p_{nf} and p_{af} using the extended DMAE approach are well matched. The probability-weighted estimates of x_k , d_k , which are calculated using Eq. (11), are shown in Fig. 3(a) and 3(b), respectively. The probability-weighted estimate of f_k (calculated using Eq. (12)) is shown in Fig. 3(c). As can be seen, x_k , d_k and f_k can all be estimated.

Example 2. In this example¹, the disturbances, which are taken from [25], are stochastic. $d_k = \begin{bmatrix} d_{1,k} \\ d_{2,k} \end{bmatrix}$ is gen-

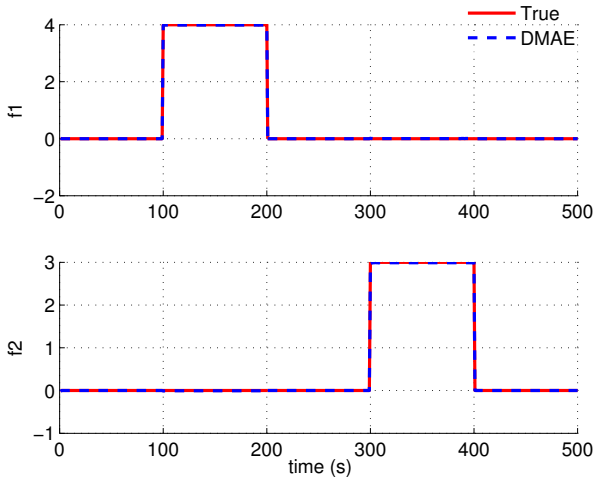
¹ The implementation of this work is available at: https://www.researchgate.net/profile/Peng_Lu15/publications?pubType=dataset



(a) True and estimated states, example 1



(b) True and estimated disturbances, example 1



(c) True and estimated faults, example 1

Fig. 3. Results of the DMAE approach, example 1

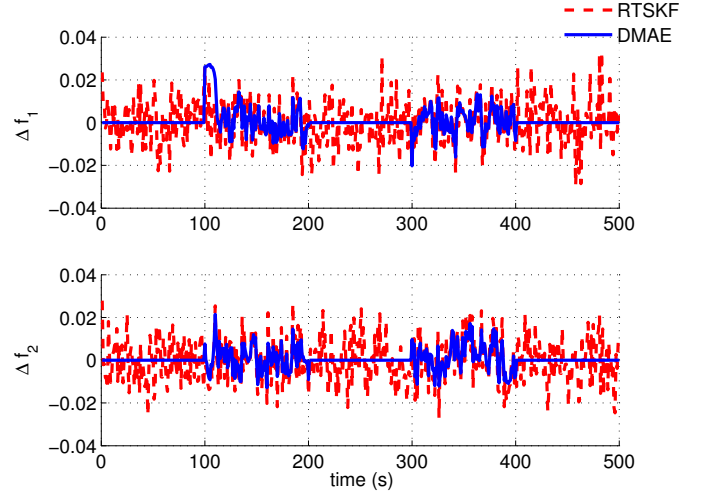


Fig. 4. Errors of estimation of f_1 and f_2 using the RTSKF and the DMAE approach, case 1, example 2

erated using the following model [25]:

$$\begin{bmatrix} d_{i,k} \\ d'_{i,k} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\frac{V^2}{L_{gi}^2} & -2\frac{V}{L_{gi}} \end{bmatrix} \begin{bmatrix} d_{i,k-1} \\ d'_{i,k-1} \end{bmatrix} + \begin{bmatrix} \sigma_i \sqrt{\frac{3V}{L_{gi}}} \\ (1 - 2\sqrt{3})\sigma_i \sqrt{\left(\frac{V}{L_{gi}}\right)^3} \end{bmatrix} w'_{d,k}, \quad i = 1, 2 \quad (70)$$

where $V = 35$, $\sigma_1 = 0.5$, $\sigma_2 = 0.8$, $L_{g1} = 2500$, $L_{g2} = 1500$ and $w'_{d,k} \sim N(0, 1)$. The generated d_k is shown by the red solid lines in Fig. 5(b). It should be noted that the DMAE approach still models d_k as a random walk process since d_k is treated as an unknown input.

Three cases are considered for this example. The first two cases are special cases. In these two cases, the existence condition (5) is satisfied. Therefore, some of the approaches mentioned in the introduction can still be used.

Case 1 $d_k = 0$, $f_k \neq 0$

In this case, E_k is a zero matrix. Therefore, condition (5) is satisfied. The probability-weighted estimate of f_k using the extended DMAE is the same as in Fig. 3(c). The RTSKF in Gillijns and De Moor [12] is also applied and the errors of estimation of f_k compared to the DMAE are shown in Fig. 4. In addition, particle filters [13,8] are also applied. The model used for estimation of f_k is also the random walk. 100 particles are used. The root mean square errors (RMSEs) of estimation of f_1 and f_2 using the RTSKF, the particle filter [13,8] and the extended DMAE are shown in Table 1.

Case 2 $d_k \neq 0$, $f_k = 0$

Table 1
RMSEs of the fault and disturbance estimation for Example 2

	Methods	d_1	d_2	f_1	f_2
Case 1	RTSKF [12]	-	-	0.0103	0.0102
	PF [13,8]	-	-	0.1549	0.1496
	DMAE	-	-	0.0060	0.0047
Case 2	OTSKF [18]	0.0697	0.1442	-	-
	PF [13,8]	0.1088	0.2035	-	-
	DMAE	0.0709	0.1459	-	-
Case 3	[12,11,18,13,8,15]	N/A	N/A	N/A	N/A
	DMAE	0.0845	0.1655	0.0230	0.0283

In this case, F_k is a zero matrix. Therefore, condition (5) is also satisfied. The true and estimated p_{nf} and p_{af} using the extended DMAE approach are shown in Fig. 5(a). The probability-weighted estimate of d_k is presented in Fig. 5(b). The results using the methods in Heish [15], Heish and Chen [18], and Gillijns and De Moor [11], are similar to that of the DMAE. Particle filter is also applied. The model used for estimation of d_k is the random walk. The RMSEs of estimation of d_1 and d_2 using the OTSKF in Heish [18], the particle filter [13,8] and the extended DMAE are shown in Table 1.

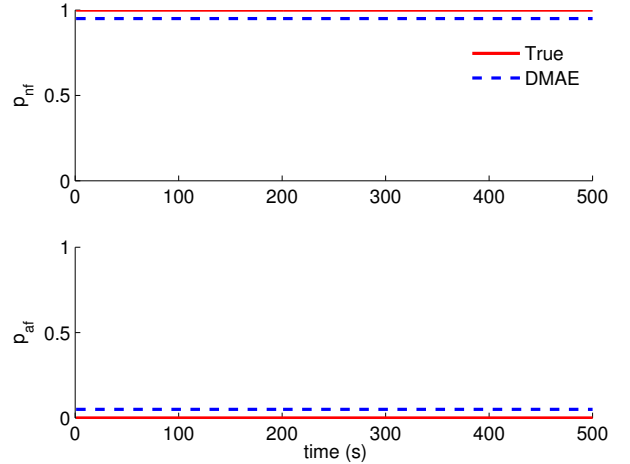
Case 3 $d_k \neq 0, f_k \neq 0$

In this case, condition (5) is not satisfied. Thus, all the conventional filters mentioned in the introduction are not applicable.

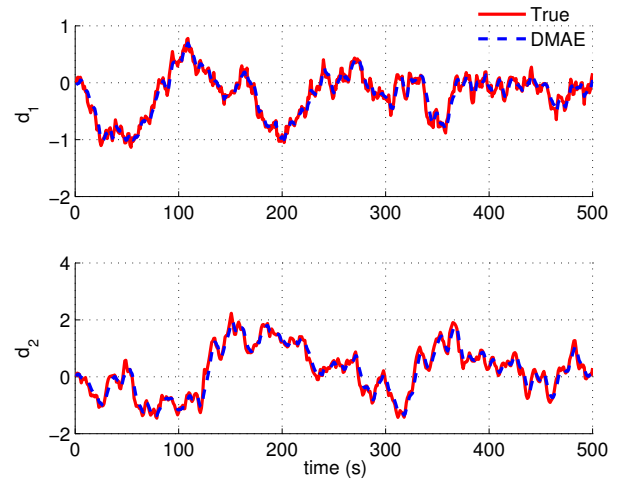
The true and estimated p_{nf} and p_{af} using the extended DMAE approach are also well matched. The probability-weighted estimates of x_k , is shown in Fig. 6. The probability-weighted estimates of d_k and f_k are the same as in Figs. 5(b) and 3(c) respectively. It can be seen that despite the fact that the existence condition for traditional unknown-input decoupled filters is not satisfied, x_k , d_k and f_k can all be estimated using the extended DMAE approach. The RMSEs of the estimation of d_k and f_k using the extended DMAE approach are shown in Table 1.

Finally, the sensitivity of the DMAE with respect to errors in Q_k and R_k is discussed. To demonstrate the sensitivity with respect to errors in Q_k , R_k is fixed and Q_k is multiplied with a coefficient k_Q . The sensitivity result of the RMSE of fault estimation with k_Q ranging from 10^{-3} to 10^3 is shown in Fig. 7(a). To show the sensitivity with respect to R_k errors, Q_k is fixed and R_k is multiplied with a coefficient k_R . The sensitivity result of the RMSE of fault estimation with k_R ranging from 10^{-3} to 10^3 is shown in Fig. 7(b).

It can be seen from Fig. 7(a) and 7(b) that the minimum RMSEs are obtained when $k_Q = 1$ or $k_R = 1$.



(a) True and estimated model probabilities, case 2, example 2



(b) True and estimated disturbances, case 2, example 2

Fig. 5. Results of the DMAE approach, case 2, example 2

However, it is also noted that the extended DMAE approach is more sensitive to R_k errors. The RMSE of the fault estimation increases to 0.063 when Q_k is multiplied with 10^3 and increases to 1.79 when R_k is multiplied with 10^3 . This is expected since in section 3, the process noise $\bar{w}_{nf,k}$ is adapted while the output noise v_k is not adapted. Therefore, selection of R_k should be performed with more caution.

6 Conclusion

In this paper, the unknown input decoupling problem is extended to the case when the existence condition of traditional unknown input filters is not satisfied. It is proved that the states, disturbances and faults can be estimated using an extended DMAE approach which does not require the existence condition. Therefore, it can be applied to a wider class of systems and applications.

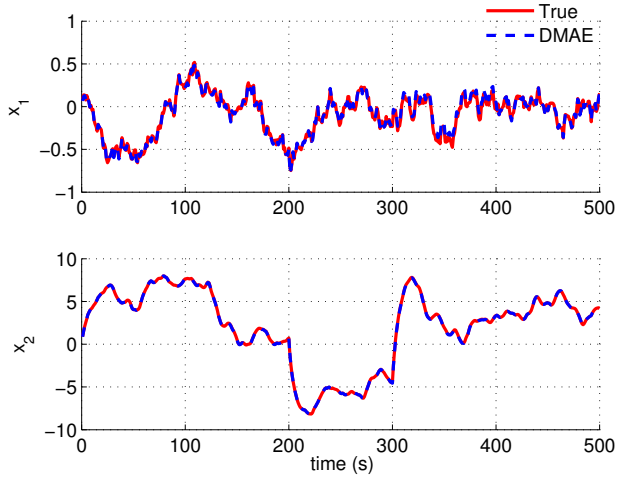
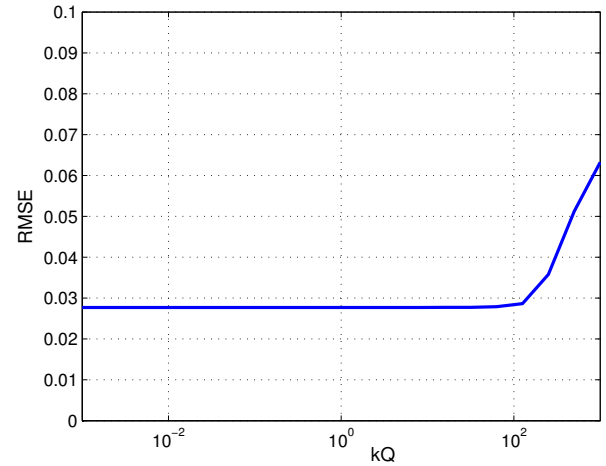


Fig. 6. True and estimated states, case 3, example 2

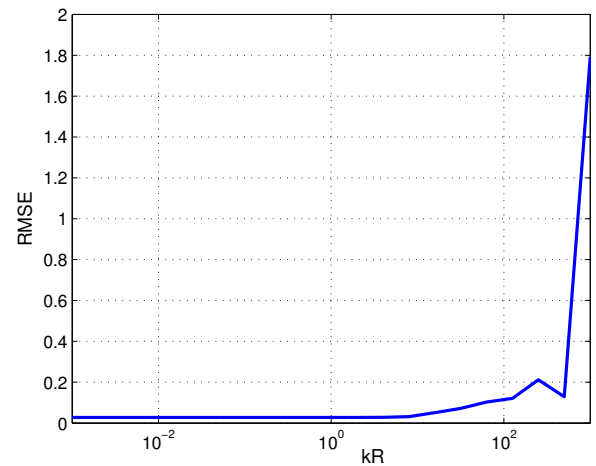
Two illustrative examples demonstrate the effectiveness of the extended DMAE approach. Future work would consider extending the DMAE to deal with systems with non-Gaussian noise.

References

- [1] Fayçal Ben Hmida, Karim Khémiri, José Ragot, and Moncef Gossa. Unbiased Minimum-Variance Filter for State and Fault Estimation of Linear Time-Varying Systems with Unknown Disturbances. *Mathematical Problems in Engineering*, 2010:1–17, 2010.
- [2] François Caron, Manuel Davy, Emmanuel Duflos, and Philippe Vanheeghe. Particle Filtering for Multisensor Data Fusion With Switching Observation Models: Application to Land Vehicle Positioning. *IEEE Transactions on Signal Processing*, 55(6):2703–2719, 2007.
- [3] Jie Chen and Ron J. Patton. Optimal Filtering and Robust Fault Diagnosis of Stochastic Systems with Unknown Disturbances. *IEEE Proceedings Control Theory and Applications*, 143:31–36, 1996.
- [4] Yue Cheng, Hao Ye, Yongqiang Wang, and Donghua Zhou. Unbiased Minimum-Variance State Estimation for Linear Systems with Unknown Input. *Automatica*, 45(2):485–491, February 2009.
- [5] M. Darouach and M. Zasadzinski. Unbiased Minimum Variance Estimation for Systems with Unknown Exogenous Inputs. *Automatica*, 33(4):717–719, 1997.
- [6] M. Darouach, M. Zasadzinski, O.A. Bassong, and S. Nowakowski. Kalman Filtering with Unknown Inputs via Optimal State Estimation of Singular Systems. *International Journal of Systems Science*, 26(10):2015–2028, October 1995.
- [7] M. Darouach, M. Zasadzinski, and M. Boutayeb. Extension of Minimum Variance Estimation for Systems with Unknown Inputs. *Automatica*, 39(5):867–876, May 2003.
- [8] Arnaud Doucet, Simon Godsill, and Christophe Andrieu. On Sequential Monte Carlo Sampling Methods for Bayesian Filtering. *Statistics and Computing*, 10:197–208, 2000.
- [9] Nando De Freitas. Rao-Blackwellised Particle Filtering for Fault Diagnosis. In *Proceedings IEEE Aerospace Conference*, pages 4–1767–4–1772, 2002.



(a) Sensitivity with respect to Q_k errors, case 3, example 2



(b) Sensitivity with respect to R_k errors, case 3, example 2

Fig. 7. Sensitivity of the fault estimation using the DMAE approach with respect to Q_k and R_k errors, case 3, example 2

- [10] Bernard Friedland. Treatment of Bias in Recursive Filtering. *IEEE Transactions on Automatic Control*, 14(4):359–367, 1969.
- [11] Steven Gillijns and Bart De Moor. Unbiased Minimum-Variance Input and State Estimation for Linear Discrete-Time Systems. *Automatica*, 43(1):111–116, January 2007.
- [12] Steven Gillijns and Bart De Moor. Unbiased Minimum-Variance Input and State Estimation for Linear Discrete-Time Systems with Direct Feedthrough. *Automatica*, 43(5):111–116, May 2007.
- [13] N.J. Gordan, D.J. Salmond, and A.F.M. Smith. Novel Approach to Nonlinear/non-Gaussian Bayesian State Estimation. In *Proc. Inst. Elect. Eng., F*, volume 140, pages 107–113, 1993.
- [14] M. Hou and R. J. Patton. Optimal Filtering for Systems with Unknown Inputs. *IEEE Transactions on Automatic Control*, 43(3):445–449, 1998.
- [15] Chien-Shu Hsieh. Robust Two-Stage Kalman Filters for

- Systems with Unknown Inputs. *IEEE Transactions on Automatic Control*, 45(12):2374–2378, 2000.
- [16] Chien-Shu Hsieh. Extension of unbiased minimum-variance input and state estimation for systems with unknown inputs. *Automatica*, 45(9):2149–2153, September 2009.
- [17] Chien-Shu Hsieh. On the Global Optimality of Unbiased Minimum-variance State Estimation for Systems with Unknown Inputs. *Automatica*, 46(4):708–715, April 2010.
- [18] Chien-Shu Hsieh and Fu-Guang Chen. Optimal solution of the two-stage Kalman filter. *IEEE Transactions on Automatic Control*, 44(1):194–199, 1999.
- [19] A. H. Jazwinski. Adaptive Filtering. *Automatica*, 5:475–485, 1969.
- [20] Simon J. Julier and Jeffrey K. Uhlmann. A New Extension of the Kalman Filter to Nonlinear Systems. in *Proc. AeroSense: 11th Int. Symp. Aerospace/Defense Sensing, Simulation and Controls*, pages 182–193, 1997.
- [21] Peter K. Kitanidis. Unbiased Minimum-variance Linear State Estimation. *Automatica*, 23(6):775–778, 1987.
- [22] Peng Lu, Laurens Van Eykeren, E. van Kampen, Cornelis Coen de Visser, and Qiping Chu. Double-Model Adaptive Fault Detection and Diagnosis Applied to Real Flight Data. *Control Engineering Practice*, 36:39–57, March 2015.
- [23] D. T. Magill. Optimal Adaptive Estimation of Sampled Stochastic Processes. *IEEE Transactions on Automatic Control*, 10(4):434–439, 1965.
- [24] Peter S. Maybeck. Multiple Model Adaptive Algorithms for Detecting and Compensating Sensor and Actuator/Surface Failures in Aircraft Flight Control Systems. *International Journal of Robust and Nonlinear Control*, 9(14):1051–1070, December 1999.
- [25] Donald Mclean. *Automatic Flight Control Systems*. Englewood Cliffs, NJ: Prentice-Hall, 1990.
- [26] Raman K. Mehra. On the Identification of Variances and Adaptive Kalman Filtering. *IEEE Transactions on Automatic Control*, 15(2):175–184, April 1970.
- [27] Sang Hwan Park, Pyung Soo Kim, Oh-kyu Kwon, and Wook Hyun Kwon. Estimation and Detection of Unknown Inputs Using Optimal FIR Filter. *Automatica*, 36:1481–1488, 2000.
- [28] Vandi Verma, Geoff Gordon, Reid Simmons, and Sebastian Thrun. Real-Time Fault Diagnosis. *IEEE Robotics & Automation Magazine*, 11(1):56–66, 2004.
- [29] Qijun Xia, Ming Rao, Yiqun Ying, and Xuemin Shen. Adaptive Fading Kalman Filter with an Application. *Automatica*, 30(8):1333–1338, 1994.
- [30] Bo Zhao, Roger Skjetne, Mogens Blanke, and Fredrik Dukan. Particle Filter for Fault Diagnosis and Robust Navigation of Underwater Robot. *IEEE Transactions on Control Systems Technology*, 22(6):2399–2407, 2014.