



# The joint optimal filtering and fault detection for multi-rate sensor fusion under unknown inputs



Hang Geng<sup>a,b</sup>, Yan Liang<sup>a,b,\*</sup>, Feng Yang<sup>a,b</sup>, Linfeng Xu<sup>a,b</sup>, Quan Pan<sup>a,b</sup>

<sup>a</sup>School of Automation, Northwestern Polytechnical University, Xi'an, China

<sup>b</sup>Key laboratory of Information Fusion Technology, Ministry of Education, Xi'an, China

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## ABSTRACT

In multi-sensor fusion, it is hard to guarantee that all sensors have an identical sampling rate, especially in the distributive and/or heterogeneous case. Meanwhile, stochastic noise, unknown inputs (UIs), and faults may coexist in complex environment. To this end, we propose the problem of joint optimal filtering and fault detection (FD) for multi-rate sensor fusion subject to UIs, stochastic noise with known covariance, and faults imposed on the actuator and sensors. Furthermore, the new scheme of optimal multi-rate observer (MRO) is presented and applied to detect faults. The observer parameters are determined optimally in pursuit of the UI decoupling and maximizing noise attenuation under the causality constraint due to multi-rate nature. Finally, the output estimation error of the MRO is used as a residual signal for FD via a hypothesis test in which the threshold is adaptively designed according to the MRO parameters. One numerical example is given to show the effectiveness of our proposed method.

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## 1. Introduction

In many complex systems such as the multi-sensor fusion system it is often unrealistic to guarantee all sensors operating at one common rate [1]. For example, for signals with different bandwidths, better trade-offs between performance and implementation cost can be obtained using A/D and D/A converters at different rates. Besides, for processed/estimated quantities, sometimes users may specify rates which are different from the sampling rates of sensors. Therefore the issue on multi-rate data fusion arises and has been paid much attention especially in the past decade.

The main challenge in conditioning monitoring systems of multi-sensor fusion system is FD, which is the precondition of reliable multi-rate fusion. Generally speaking, a FD process consists of constructing a residual signal which can then be compared with a pre-defined threshold. When the residual signal exceeds the threshold, the fault is detected and an alarm is generated. However, most of the existing researches about FD for multi-rate sensor fusion systems are limited to the scope of deterministic systems, i.e., the stochastic noises do not exist in either the state equation or output equation. In fact, stochastic noises are commonly considered in state evolution and sensor sampling in the field of data fusion. Furthermore, the fil-

tering and FD for multi-rate sensor fusion are treated as two separate problems in the existing results while these problems are coupled and hence should be jointly considered. Motivated by the above observations, we investigate the problem of joint optimal filtering and FD of multi-rate sensor fusion in the presence of UIs, noises and faults.

In this paper, we first present a new optimal MRO with its state estimation UI decoupled and noise attenuated. To detect faults, the output estimation error of the MRO is used as a residual. The MRO parameters are determined through decoupling the residual with the UI and minimizing the effect of the noise on the residual in the minimum mean square error (MMSE) sense. The disturbance decoupling and noise attenuation conditions are found to be closely related with sensor rates and the causality constraint due to multi-rate nature. The residual is evaluated via a hypothesis test in which the detection threshold is adaptively determined. The main contributions are listed as follows:

- the developed optimal MRO is UI-decoupled and noise-attenuated. In other words, the decoupled UI has no effect on FD while minimizing the noise effect results in the accurate and adaptive design of detection threshold;
- the existence condition of the UI-decoupling is explored, which will supply the guidance of sensor type, sampling rate and sensor networking;
- the optimal observer parameters are derived in the sense of minimizing noise effect on FD. It results in adaptive design of detection threshold;

\* Corresponding author at: School of Automation, Northwestern Polytechnical University, Xi'an, China. Tel.: +86 2988431308.

E-mail addresses: [genghang@mail.nwpu.edu.cn](mailto:genghang@mail.nwpu.edu.cn) (H. Geng), [liangyan@nwpu.edu.cn](mailto:liangyan@nwpu.edu.cn) (Y. Liang), [yangfeng@nwpu.edu.cn](mailto:yangfeng@nwpu.edu.cn) (F. Yang), [xulinfeng@nwpu.edu.cn](mailto:xulinfeng@nwpu.edu.cn) (L. Xu), [quanpan@nwpu.edu.cn](mailto:quanpan@nwpu.edu.cn) (Q. Pan).

## Nomenclature

$I_m$	the identity matrix with $m \times m$ dimensions
$O_m$	the zero matrix with $m \times m$ dimensions
$E\{ \cdot \}$	the operator of mathematical expectation
$\text{diag}\{ \cdot \}$	the diagonal matrix
$\text{prob}\{ \cdot \}$	the probability measure
$\text{rank}\{ \cdot \}$	the matrix rank
$A_{i,j}$	the $(i, j)$ -th element of $A$
$\mathbf{1}_N$	the $N$ -dimensional vector with each element being 1
$\otimes$	the Kronecker product
$\hat{\cdot}$	the estimate of a random vector
subscript $j$	the matrix or variable related to the $j$ -th sensor
superscripts $-1, T, +$	the inverse, transpose, and Moore–Penrose operations, respectively
superscripts $u, d, w, s$	the matrix or variable related to the known input, UI, noise and sensor, respectively
$x_k, u_k, d_k, w_k, f_k^a$	the state, known input, UI, process noise and actuator fault vectors, respectively
$y_{j,n_jk}, v_{j,n_jk}, f_{j,n_jk}^s$	the measurement, measurement noise and sensor fault vector of the $j$ -th sensor, respectively
$z_k, e_k, r_k$	the observer state, estimation error and residual vectors, respectively
$A, C_j, E_j$	the state matrix, measurement matrix and sensor fault matrix, respectively
$F_k, T_k, K_k, H_k$	the observer parameter matrices

- the joint optimal filtering and FD has bigger computation costs than separate filtering or FD. Fortunately, the computation-intensive parameter design can be implemented off-line, and the online calculation only contains simple estimate update and threshold setting.

This paper is organized as follows. The related work is briefly reviewed in Section 2 and the problem is formulated in Section 3. Section 4 describes the scheme of the joint optimal filtering and FD. It includes the MRO design, residual generation and residual evaluation. Section 5 demonstrates the effectiveness of the proposed scheme in two sets of experiments, and some conclusions are drawn in Section 6.

## 2. Related work

Multi-sensor data fusion is a technology to enable combining information from several sources in order to form a unified picture of the environment. Definitely, the estimation and detection are the main topics of data fusion.

Regarding the multi-rate sensor fusion, much attention has been paid, especially in the last decade. The state estimation approach based on dual-rate sensor measurements was proposed in [2] and extended to deal with the asynchronous multi-rate sensor measurements, where the ratio between the sampling rates of different sensors was allowed to be any positive integer [3]. Accounting for out of sequence data and latent data, general asynchronous fusion estimation methods were put forward for multi-sensor systems [4,5]. Since different dynamic models always have different frequency properties in multiple model systems, the fast-rate sensor measurement was thus compressed to a slow-rate one with little or no accuracy degradation in low-frequency models, and hence results in multi-rate in-

teracting multiple model estimators [6] and its target-tracking application to out-of-sequence GMTI data [7] or distributed fusion [8]. In the case that the updating rate of state estimates is different from the measurement sampling rate, the wavelet-transformation-based and the optimal  $H_2/H_\infty$ -based estimation schemes were proposed in [9] and [10], respectively. A linear minimum variance estimator was proposed for the four-rate estimation problem with the state updating rate, the measurement sampling rate, the estimate updating rate, and the estimate output rate [11]. For systems having measurement missing or packet losses, a multi-rate  $H_\infty$  method [12] and a two-stage distributed fusion estimation method [13] were given, respectively. The optimal LMV estimators were designed for both centralized and decentralized fusion the case of multi-rate packet dropouts [14]. In addition, the multi-sensor fusion estimation scheme for wireless sensor networks (WSNs) with nonuniform estimation rates were concerned and two fusion algorithms that can fuse available local estimates generated at different time scales were provided, allowing estimation rates at different sensors to be different from each other [15]. In general, no fault is considered in the above research.

Concerning the FD problem in multi-rate sensor systems with UI in the state equation, the lifting technique was used to convert the multi-rate system into a linear time-invariant (LTI) model with slow sampling rate, based on which residual generators were designed using state observers [16] and [17], but the residual can only be updated at the same rate as the LTI model, and hence results the slow-rate fault detection. For fast-rate residual generation, a bank of observers with different rates were designed where each observer was specialized for the corresponding sensor [18]. For multi-rate systems with UI appeared in the state equation and output equation, in order to maximize while minimize the influence of the UI on the residual, a parity-space based residual generator [19] and  $H_\infty$  optimal and causal residual generators were proposed [20]. For the case of norm-bounded UI, an observer-based fault detection filter was presented for residual generation and the residual was obtained by solving an  $H_\infty/H_\infty$  or  $H_\infty/H_-$  optimization problem [21]. The aforementioned works here, however, are unable to deal with stochastic uncertainties, i.e., the noise.

In addition, in the context of sensor networks, the random network-induced phenomena become even severe due primarily to the network size, communication constraints, limited battery storage, strong coupling, spatial deployment, and source correlation [22]. Some important progresses on dealing with such network-induced uncertainties have been made, including random delays, packet dropout, data missing etc. [23–32]. In principle, the network-induced uncertainties with known statistics may be reformulated as the equivalent noises with known covariance via model transformation, and the network-induced uncertainties with unknown evolution information may be treated as UIs. In other words, it is possible to extend our obtained result here to the case under multiple network-induced uncertainties, which is an interesting but still open problem.

## 3. Problem formulation

Here we formulate the joint optimal filtering and FD problem of multi-rate sensor fusion systems with both deterministic and stochastic uncertainties as shown in Fig. 1, which consists of the following three parts. In the dynamic system part, the state evolution is driven by the known input and unknown uncertainties such as the UI, noise and possible actuator faults. In the multi-rate sensor part, measurements are sampled by multiple sensors with distinct rates and corrupted by both measurement noise and possible sensor faults. Here all sensors work synchronously, and no time delay or packet dropouts are considered. In the fusion center, multi-rate sensor measurements are processed by the multi-rate observer, residual generation, and decision making in order to output the state estimate and

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