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Fault Detection and Isolation Method in Decentralized Kalman Filter

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***Abstract:** This paper answers several questions of centralized Kalman-Filters in multi-sensorfusion, fault detection we saw sensor drift problem that is expected to be solved by an additional system able to detect a drift as a sensors fault. The drift gives a fault in state estimation. Hence this paper deals with developing and simulating a traditional concept of fault detection and isolation, FDI, algorithm used in MATLAB simulations, where a nodal structure of decentralized Kalman filter is assumed and consist of three sensors/nodes. The FDI as an additional algorithm improves on DKF based structure to avoid sensors' failures. The DKF model with FDI Testing the FDI implemented in DKF structure with one failed sensor system.*

***Keywords:** Kalman-Filter, Multi-sensorfusion, MATLAB Simulations, DKF, FDI, Nodes, Algorithm, Fault detection.*

I. INTRODUCTION

In this paper, the FDI algorithm would be used to detect a fault of an affecting sensor by an exponential drift and consequently isolate it to minimize an error caused by the fault in state estimation. The algorithm of FDI should be implemented in a self-acting technical system. The advantage of the algorithm is that every node of the decentralized structure will be able to detect and isolate fault in sensor its self. As the sensor information is propagated to all neighboring nodes by a link interconnection, the FDI algorithm is simultaneously performing fault detection in each node to improve robustness. It allows us to implement the algorithm in a real time processing. The FDI technique is developed, with an inspiration of the fault-tolerant design, and correlation based detection used to reach middle accuracy performance. Various techniques of fault detection for fault-tolerant design with diverse applications are reported. We will present the reliability and some imperfections of FDI.

A new model of linear finite-dimensional stochastic system dynamics is used

$$x(n+1)=\begin{bmatrix} 2.633 & 1 & 0 \\ -2.33 & 0 & 1 \\ 6.907\ .\ 10^{-1} & 0 & 0 \end{bmatrix} x(n)+\begin{bmatrix} 6.02\ .\ 10^{-2} \\ -1.132\ .\ 10^{-1} \\ 5.91\ .\ 10^{-2} \end{bmatrix}[u(n)+w(n)],\quad x(0)=0,$$

$$\begin{bmatrix} y_{v1}(n) \\ y_{v2}(n) \\ y_{v3}(n) \end{bmatrix}=\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} x(n)+\begin{bmatrix} v_1(n) \\ v_2(n) \\ v_3(n) \end{bmatrix}.$$

In simulations the n = 0,1,…,4000.

A time response of the observations behaves as a third order of low pass filter, and all observations $yv1(n)$, $yv2(n)$, $yv3(n)$ give incomparable quality. Therefore the system model is technically suitable for its property.

II. TESTING THE FDI IMPLEMENTED IN DKF STRUCTURE WITH ONE FAILED SENSOR

This section introduces the first example and the idea of FDI algorithm to be coupled with DKF model. a new realistic approach to the fault coupled with first sensor is found as follows:

$$\begin{bmatrix} y_{v1}(n) \\ y_{v2}(n) \\ y_{v3}(n) \end{bmatrix} = \begin{bmatrix} d_1(n) & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} x(n) + \begin{bmatrix} v_1(n) \\ v_2(n) \\ v_3(n) \end{bmatrix},$$

Where $d1(n)$ is defined by above equation with $\delta = 1500$ and $\Delta = 200$. The delta δ describes the time when the exponential drift starts. Next parameter Δ describes the slope on how quickly the drift turns down inside of the first sensor. We turn to observation processing of the first sensor because only this sensor is affected by the exponential drift.

III. FAULT DETECTION

This part presents a general idea of the fault detection algorithm executed in every processor of corresponded the i-th node. It indicates that a fault is recognized; see the flowchart below as the timing diagram.

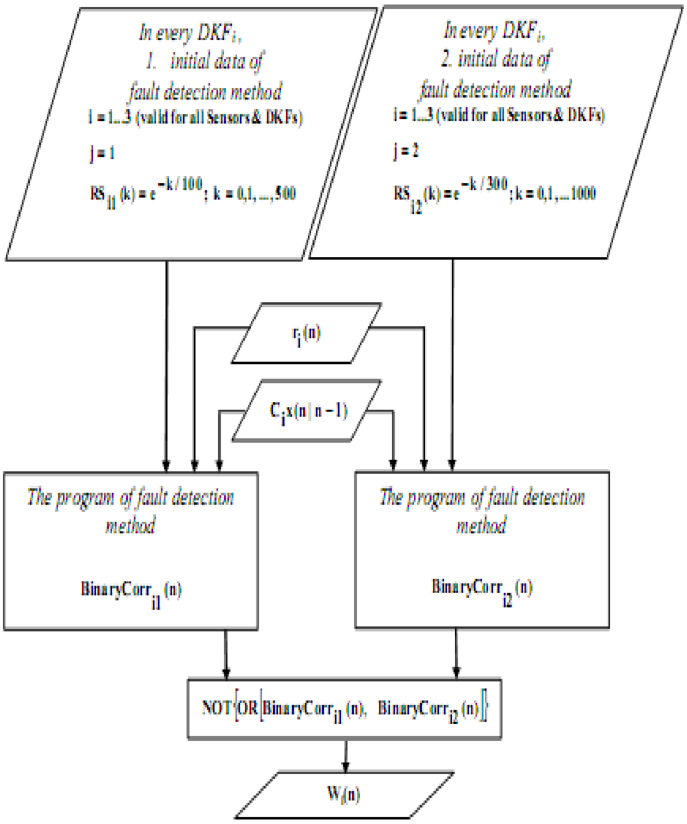


Fig3.1 : Flowchart of fault detection (FD)method

The fault detection algorithm can be divided in two stages: residual generation and decision making.

1. In the first stage, the residual and the enhanced failure effect on the residual is called the fault signature.
2. In the second stage, the procedure of decision making is needed for fault detection to decide whether a fault is presented or not in residuals.

A spurious fault is not our objective of study. The fault signature $Y1(n)$ is correlated with real drift $d1(n)$ been presented. Here the problem is that real drift $d1(n)$ is unknown for every processor in anode. Thus a presumption of possible drift profiles should be made from some previously done measurements or employed expert systems. Thus various drift models need to be created and stored in memory of each processor such as reference signals Actually, it is difficult to exactly suppose any drift profile, so that the mathematical description of every reference signal may differ from real drift $d1(n)$ but high correlation between them still exits to be suitable in fault detection. The point is that, the permanently stored reference signals and measured *Y1*(*n*) are correlated Thus the cross-correlation is high when a fault occurs because *d1*(*n*) is contained in *Y1*(*n*) and *yv1*(*n*). This procedure is performed in every node separately.

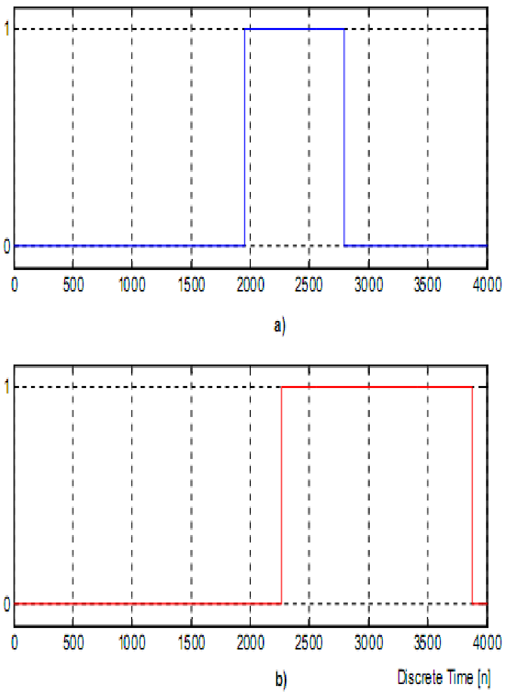


Fig3.2: Two pulses after the fault detection

IV. FAULT ISOLATION

This part presents the FI algorithm to the important theme of sensor validation in decentralized structure in multi-sensor fusion. Of course generally, a major number of sensors can be affected by a drift at the same time.

The main focus on fault isolation is based on variance error information ***VEI****i*(*n*) and state error information ***SEI****i*(*n*) validation. These two matrices are usually corrupted by a fault while the *i*-th sensor is affected by a drift. During successful fault detection, the corrupted ***VEI****i*(*n*) and ***SEI****i*(*n*) matrices would be isolated only by the node wherein its corresponding sensor has been found incorrect by FD program implemented inside of a corresponding node. The *Wi*(*n*) results two instances as below

$$W_i(n) = \begin{cases} 0, \text{when fault detected} \\ 1, \text{when no fault detected} \end{cases}.$$

In DKF estimator of every node the ***VEI****i*(*n*) and ***SEI****i*(*n*) are replaced by the matrix multiplications *Wi* (*n*)***VEI*** *i* (*n*) and *Wi* (*n*)***SEI*** *I*

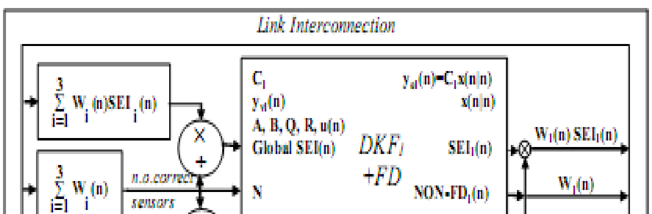


Fig 4.1: DKF with fault detection system inside and isolation

Every block of processor is denoted by DKFi+FD. An outage part of Figure performs the fault isolation. Thus the FI crosses matrices VEIi(n), SEIi(n) via the weighting factor Wi(n) when necessary. Then a number of correctly performing sensors is lower than the total number of sensors if a failure occurs.

V. Testing the FDI Implemented in DKF Structure with two failed sensor

Iteration Time n = 1,2,3,…

This section deals with the same example as previous one, but the first two sensors are affected by two different drifts and one sensor remains correctly doing. The observations model is defined as:

$$\begin{bmatrix} y_{v1}(n) \\ y_{v2}(n) \\ y_{v3}(n) \end{bmatrix} = \begin{bmatrix} d_1(n) & 0 & 0 \\ 0 & d(n) & 0 \\ 0 & 0 & 1 \end{bmatrix} x(n) + \begin{bmatrix} v_1(n) \\ v_2(n) \\ v_3(n) \end{bmatrix},$$

Where the time 4000 ..., , 1 , 0 = n remains unchanged in simulation. The drift d1(n) is taken with 1500 = δ.. The time behaviours of the drifts are shown in below.

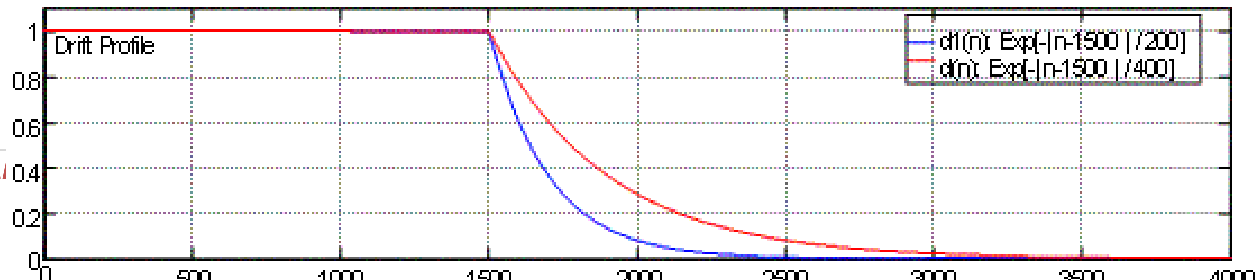


Fig 5.1 : Drifts d1(n) and d(n)

VI. Conclusion

The major requirement on this fault detection and isolation, FDI, algorithm is an availability to multiple observations. We have shown on how to apply FDI algorithm to the problem of faults in sensors. The FDI algorithm has been found out in three strategies:

1. Exercising on fault detection method, FD
2. Exercising on fault isolation method, FI.

The all algorithm is tailor-made on system dynamics and the knowledge of drift in sensors.

Firstly the question related to one affected sensor will be answered below. Our simulation results show that the DKF model with FDI algorithm yields 75% reliability of FDI performance insomuch that a pure DKF model without FDI provides exactly 0% reliability.

The FDI reliability is not meant to be state estimation accuracy, although its relative MSE is about 0.01. In case of high process noise, results of simulations show about 70% reliability of FDI algorithm. The five percentage aggravation is caused by 100- times higher power of process noise, where the cross-correlation function used in FDI system is disturbed by that.

Having two sensors affected by exponential drifts, the FDI reliability rises up to 84% which describes the benefit of FDI. But considering 100-times higher power of process noise, the reliability is reduced down to 54% and relative MSE of state estimation is about 0.11. This is the FDI imperfection with major number of corrupted sensors. Two failed sensors out of three total sensors and having high power of process noise result in loss of performance of FDI. So said, the FDI functionality is correct as long as a number of affected sensors is minor otherwise the DKF may be at risk.

The reliability of FDI describes on how much lost energy in $\mathbf{x}(n \mid n)$ is compensated back rather than the pure DKF without FDI cannot perform.

The answer of fault detection and isolation algorithm has been recently given above.

VII. Results

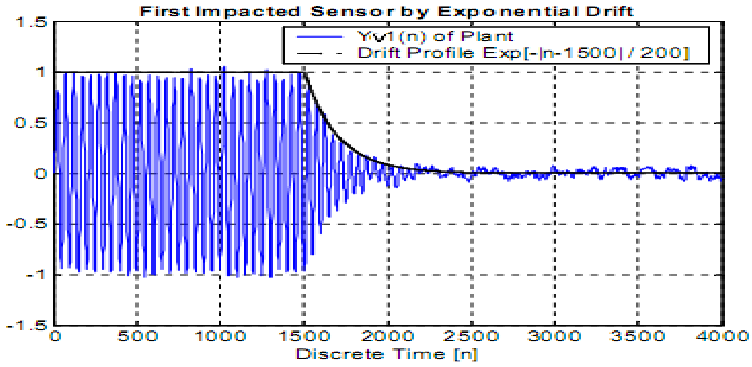


Fig 7.1 : First corrupted sensor by exponential drift

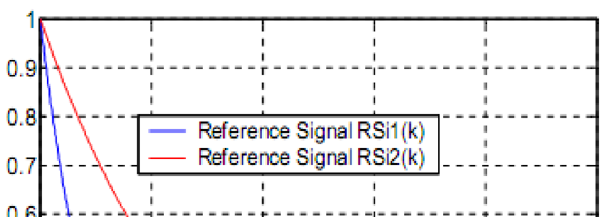


Fig7.2 : Reference signals RS11(k) and RS12(k)

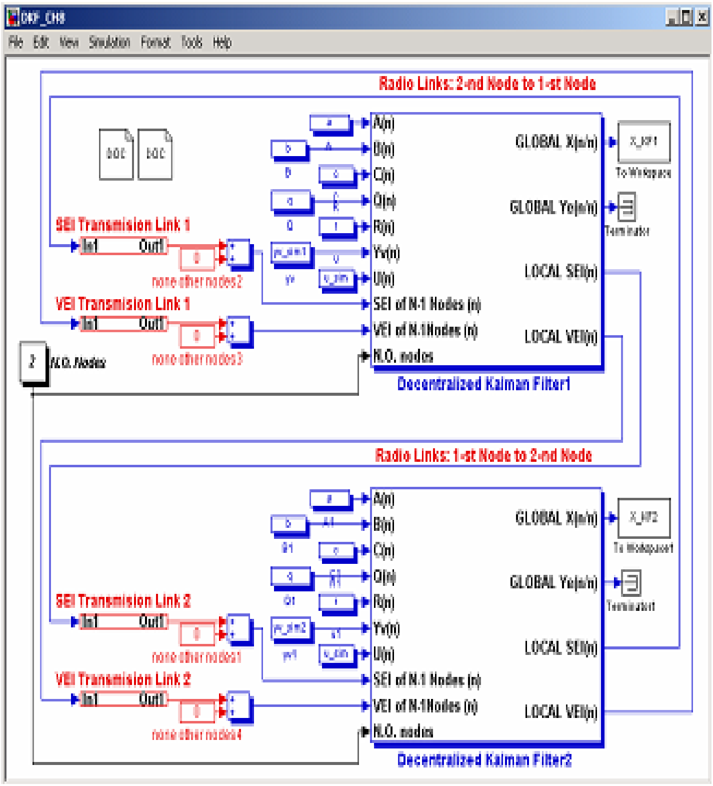


Fig7.3: Two Nodes KF model

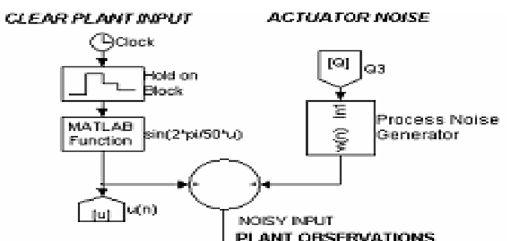
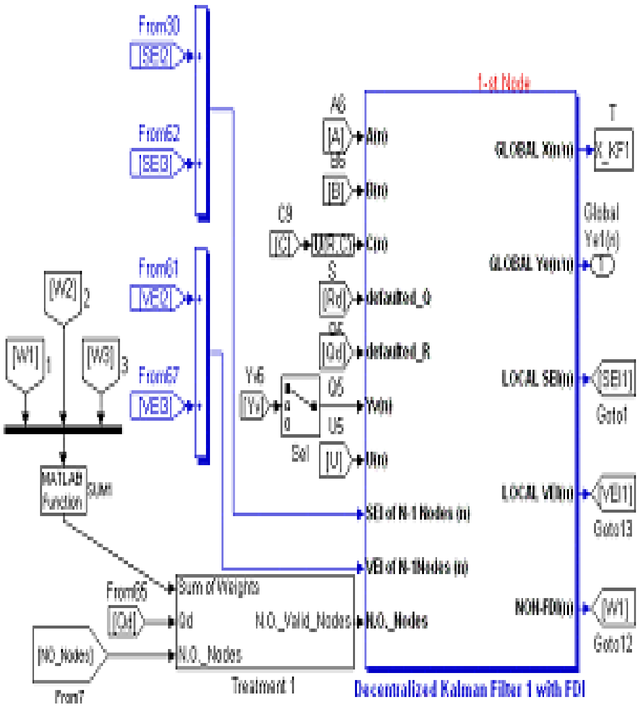


Fig7.4 : Test of two Nodes DKF model



7.5: First Node Block connection of DKF with FDI Figure

References

1. GOODWIN Clifford G. and SIN K. S. (1984). “Adaptive Filtering Prediction and Control,” PRENTICE-HALL, INC., Englewood Cliffs, New Jersey 07632.

2. FRIEDLAND B. (1996). “Advanced Control System Design,” PRENTICE-HALL, INC., A Simon & Schuster Company Englewood Cliffs, New Jersey 07632

3. GELB A., KASPER J. F., NASH R. A., PRICE C. F., and SUTHERLAND A. A., (1999). “Applied Optimal Estimation,” Massachusetts Institute of Technology Cambridge, Massachusetts, and London, England, Library of Congress Catalog Card Number:741604.

4. MOHINDER S. GREWAL and ANGUS P. ANDREWS, (1993). “KALMAN FILTERING Theory and Practice,” PRENTICE-HALL, INC., A Simon & Schuster Company Englewood Cliffs, New Jersey 07632.

5. FRANK L. LEWIS, and VASSILIS L. SYRMOS, (1993). “OPTIMAL CONTROL,” A Wiley- Interscience Publication, A John Wiley & Sons Inc., New York, Chichester, Brisbane, Toronto, Singapore.

6. ISERMANNR. (Rolf), (2003). “Mechatronic Systems: fundamentals,” 1.Mechatronics and Micro electro mechanical systems, British Library Cataloguing in Publication Data.

7. MATLAB Release 12 Help.

8. VERHAEGEN M. H., (March 1989). “Improved understanding of the loss-of-symmetry phenomenon in the conventional Kalman filter,” Automatic Control, IEEE Transactions, Vol.34, Iss.3, pp. 331-333.