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Fault Detection and Diagnosis of Dynamic Systems with Colored Measurement Noise

유색측정잡음을 갖는 동적 시스템의 고장검출 및 진단

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Abstract

An effective scheme to detect and diagnose multiple failures in a dynamic system is described for the case where the measurement noise is correlated sequentially in time. It is based on the modified interacting multiple model (MIMM) estimation algorithm in which a generalized decorrelation process is developed by employing the autoregressive (AR) model for the colored noise and applying measurement difference method.

Keywords: IMM, Kalman filter, FDD, colored measurement noise, steam generator

요 약

측정잡음이 시간에 순차적으로 상관된 경우의 동적 시스템에서의 다중 고장들을 검출하고 진단하는 효과적인 방법을 제시하였다. 제안된 고장검출 및 진단기법은 수정된 상호간섭다중모델 추정 알고리즘을 기반으로 하며, 이것은 유색잡음에 대해 자기회귀 모델을 사용하고 측정 차분법을 적용함으로써 일반 비상관 프로세스를 설계하여 상호간섭다중모델 추정 알고리즘에 적용한 것이다.

I. Introduction

Modern dynamic systems are becoming more and more sophisticated. Consequently, there is a growing demand for their reliability and security. To assure the reliability and security of the system, it is essential to rapidly and reliably detect and isolate its sensor, actuator, or system component failures.

Over the past two decades, fault detection and diagnosis (FDD) techniques have received much attention from both theoretical and practical points of view. Many schemes have been developed in the literature for the FDD of dynamic systems [1-5, 8]. In general, the FDD techniques developed so far may be classified into two categories: The one is the model-based approach which makes use of a mathematical model of the system or of parts of it, and the other is the knowledge-based approach where the analytical model of the system is not available [4-6].

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More recently, the promising model-based FDD approaches have been developed based on the use of multiple models (MMs) for the dynamic systems [7-11]. It runs a bank of the Kalman-type filters in parallel, each based on a model matching to a particular mode of the system. Among the MM based FDD approaches, the interacting multiple model (IMM) based FDD approach [12-14] is known as one of the most cost-effective (in terms of performance versus complexity) techniques for the system involving structural as well as parametric changes. The IMM algorithm is a recursive estimator and consists of a bank of Kalman filter running in parallel, a model probability evaluator, an estimate mixer at the input of each Kalman filter, and an estimate combiner at the outputs of the filters.

The performance of the FDD technique heavily depends on the accuracy of the measurement sensors. Quite often in real situations, the measurement error is correlated sequentially in time and hence the performance of the FDD techniques developed on the assumption of the white Gaussian measurement noise is degraded in the colored noise environment.

In this paper, we describe a cost-effective FDD algorithm based on the modified IMM (MIMM) approach for the case where the measurement noise is correlated sequentially in time. In doing so, the generalized decorrelation process is developed to decorrelate the high-order correlated measurement noise based on the measurement difference method. Numerical example for the nuclear steam generator is provided to illustrate the performance of the proposed FDD algorithm.

II. Dynamic model and decorrelation process

2.1 Modeling of the dynamic systems

The IMM approach to FDD assumes that the actual system at any time can be modeled sufficiently accurately by a stochastic system. Let's assume that a set of N dynamic models has been set up to approximate the actual system as follows:

$$x_{k+1} = F^j x_k + G^j u_k + T^j w_k^j \tag{1}$$

where $x_k \in \mathcal{R}^{n_x}$ and $u_k \in \mathcal{R}^{n_u}$ are the state and input vector at time k, respectively and superscript j denotes quantities pertaining to model j $(j = 1, 2, \cdots, N)$; F, G and T are the state transition matrix, control input matrix and noise gain matrix, respectively; $w_k \in \mathcal{R}^{n_w}$ is a discrete-time process noise, which is assumed zero-mean white Gaussian noise with known covariance such that

$$E[w_k w_l^T] = Q_k \delta_{kl} \tag{2}$$

where δ_{kl} is the Kronecker delta function, which is equal to 1 if $k = l$, otherwise it is zero.

In addition, the measurement equation is

$$z_k = H^j x_k + v_k^j \tag{3}$$

where $z_k \in \mathcal{R}^{n_z}$ is the measurement vector at time k and H is the measurement matrix.

In the FDD algorithms developed so far, it has been assumed that the measurement noise $v_k \in \mathcal{R}^{n_z}$ have white Gaussian distributions. However, in real situations, the measurement noise is significantly correlated in time when the measurement frequency is high. In this paper, it is assumed that the correlated measurement noise can be modeled as the nth-order Markov process such that

$$v_k = \alpha_1 v_{k-1} + \alpha_2 v_{k-2} + \cdots + \alpha_n v_{k-n} + \eta_k \tag{4}$$

where $\alpha_i \ (i = 1, 2, \cdots, n)$ is the correlation coefficient and η_k is zero-mean white Gaussian noise with covariance

$$E[\eta_k \eta_l^T] = R_{\eta_k} \delta_{kl} \quad (5)$$

And it is assumed that the process noise and the measurement noise are mutually independent such that

$$E[v_k w_l^T] = 0, \ \forall \ k \text{ and } l \quad (6)$$

2.2 Generalized decorrelation process

Since it is irrelevant to use the correlated measurement noise v_k as it is in the Kalman-type filter, it is necessary to decorrelate it. The correlated measurement noise (4) can be rearranged as:

$$-\sum_{i=0}^{n} \alpha_i v_{k-i} = \eta_k \quad (7)$$

where $\alpha_0 = -1$. To decorrelate the correlated noise, we define a new artificial (pseudo) measurement y_k based on the measurement difference as follows:

$$y_k \equiv -\sum_{i=0}^{n} \alpha_i z_{k-i} \quad (8)$$

From the state model (1), we can obtain the following equation:

$$x_{k-i} = F^{-i} x_k - \sum_{j=0}^{i} F^{-j} (G u_{k+j-(i+1)} + T w_{k+j-(i+1)}) \quad (9)$$

where $i = 1, 2, \cdots, n$. Substituting eqs. (3) and (9) into eq. (8), the following generalized decorrelation process can be obtained.

$$y_k = \overline{H} x_k + \sum_{i=1}^{n} B_i G u_{k-i} + \overline{v_k} \quad (10)$$

$$\text{where, } \overline{H} \equiv H - B_1 \quad (11)$$

$$\overline{v_k} \equiv \sum_{i=1}^{n} B_i T w_{k-i} + \eta_k \quad (12)$$

$$B_i \equiv \sum_{j=i}^{n} \alpha_j H F^{-j+(i-1)} \quad (13)$$

The new measurement noise $\overline{v_k}$ is white, but it is also correlated with the process noise w_{k-i}. In most practical situations, the first-term of right-hand side in (12) can be neglected with little degradation in performance since the covariance of $\overline{v_k}$ is dominated by the covariance of η_k. The covariance of the artificial measurement noise can be obtained as follows:

$$\overline{R_k} \equiv E[\overline{v_k}\, \overline{v_k}^T] = \sum_{i=1}^{n} B_i T Q_k T^T B_i^T + R_{\eta_k} = R_\eta \quad (14)$$

In the next section, we describe the MIMM based FDD scheme by using the generalized decorrelation process.

III. The FDD scheme based on the MIMM estimator

Basically, The FDD scheme based on the MIMM (MIMM_FDD) can be obtained directly from the IMM based FDD (IMM_FDD) scheme by including the generalized decorrelation process. For more details on the derivation of the IMM_FDD scheme, see [12-14].

The MIMM_FDD scheme is a recursive algorithm. In each cycle it consists of the following six major steps:

1) model-conditional reinitialization (interaction or mixing of the estimates), in which the input to the filter matched to a certain mode is obtained by mixing the estimates of all filters at the previous time; 2) decorrelation of the correlated measurement error; 3) model-conditioned filtering (bank of the Kalman filter), performed in parallel for each mode; 4) mode probability update, based on the model-conditional likelihood functions; 5) determination of the fault based on the mode

probability measure, and 6) estimate combination, which yields the overall state estimate as the probabilistically weighted sum of the updated state estimates of all filters.

Let the set of possible sensor and actuator failures and the normal mode be modeled by a set

$$M = [m_1, m_2, \cdots, m_N] \tag{15}$$

where m_1 stands for the normal mode and $m_2, \cdots, m_N$ denote the possible fault modes.

Based on the above mode set, the MIMM_FDD scheme can be depicted as Fig. 1.

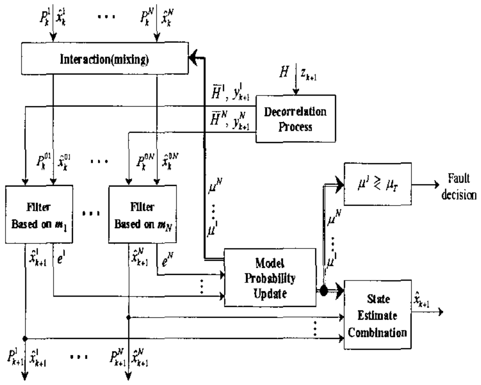


Fig. 1. Schematic diagram of the MIMM_FDD scheme.

One cycle of the MIMM_FDD algorithm can be summarized as the following 6 steps:

1) Step 1: interaction (mixing) of the estimates

· predicted mode probability:

$$\mu^j_{k+1|k} = \sum_i \pi_{ij}\mu^i_k \tag{16}$$

where π_{ij} is transition probability from mode m_i to mode m_j and μ^i_k is the probability for i-th mode.

· mixing probability:

$$\mu^{i|j}_k = \pi_{ij}\mu^i_k / \mu^j_{k+1|k} \tag{17}$$

· mixing estimate:

$$\hat{x}^{0j}_{k|k} = \sum_i \hat{x}^i_{k|k}\mu^{i|j}_k \tag{18}$$

· mixing covariance:

$$P^{0j}_{k|k} = \sum_i [P^i_{k|k} + (\hat{x}^{0j}_{k|k} - \hat{x}^i_{k|k})(\hat{x}^{0j}_{k|k} - \hat{x}^i_{k|k})^T]\mu^{i|j}_k \tag{19}$$

2) Step 2: generalized decorrelation process in (10)

3) Step 3: model-conditional Kalman filtering

· time update

$$\hat{x}^j_{k+1|k} = F^j \hat{x}^{0j}_{k|k} + G^j u_k \tag{20}$$

$$P^j_{k+1|k} = F^j P^{0j}_{k|k}(F^j)^T + T^j Q^j_k (T^j)^T \tag{21}$$

· measurement update

$$K^j_{k+1} = P^j_{k+1|k}(\overline{H}^j)^T (S^j_{k+1})^{-1} \tag{22}$$

$$\hat{x}^j_{k+1|k+1} = \hat{x}^j_{k+1|k} + K^j_{k+1} e^j_{k+1} \tag{23}$$

$$P^j_{k+1|k+1} = P^j_{k+1|k} - K^j_{k+1} S^j_{k+1} (K^j_{k+1})^T \tag{24}$$

where,

$$e^j_{k+1} \equiv y_{k+1} - (\overline{H}^j \hat{x}^j_{k+1|k} + B^j_1 G^j u_k) \tag{25}$$

$$S^j_{k+1} \equiv \overline{H}^j P^j_{k+1|k} (\overline{H}^j)^T + \overline{R}^j_{k+1} \tag{26}$$

4) Step 4: mode probability update

· likelihood function:

$$L^j_{k+1} = \frac{1}{\sqrt{2\pi |S^j_{k+1}|}} \exp\left\{ -\frac{1}{2} (e^j_{k+1})^T (S^j_{k+1})^{-1} e^j_{k+1} \right\} \tag{27}$$

· mode probability:

$$\mu^j_{k+1} = \mu^j_{k+1|k} L^j_{k+1} / \sum_i \mu^i_{k+1|k} L^i_{k+1} \tag{28}$$

5) Step 5: FDD logic

· fault decision:

$$\mu^j_{k+1} = \max_i \mu^i_{k+1} \begin{cases} > \mu_T & \Rightarrow \overline{H}^j : \text{ fault } j \text{ occured.} \\ < \mu_T & \Rightarrow \overline{H}^1 : \text{ no fault} \end{cases} \tag{29}$$

6) Step 6: combination of estimates

· overall estimate:

$$\hat{x}_{k+1|k+1} = \sum_j \hat{x}^j_{k+1|k+1} \mu^j_{k+1} \tag{30}$$

· overall covariance:

$$P_{k+1|k+1} = \sum_j [P^j_{k+1|k+1} + (\hat{x}_{k+1|k+1} - \hat{x}^j_{k+1|k+1})$$

$$(\hat{x}_{k+1|k+1} - \hat{x}^{j}_{k+1|k+1})^{T}]\mu^{j}_{k+1} \quad (31)$$

IV. Numerical example

4.1 Indices for performance evaluation

In order to evaluate the FDD performance, the following indices were used [12]: average percentages of correct detection and identification (CDID), incorrect fault identification (IFID), false alarm (FA), and missed fault detection (MFD). A CDID is obtained if the model that is closest to the system mode (normal or fault mode) in effect at the given time has a probability higher than the specific threshold $\mu_T = 0.9$. An IFID is obtained if the model with a probability over μ_T is not the one closest to the fault mode in effect at the given time. An FA is obtained if the model with a probability over μ_T is not the normal mode while the normal mode is in effect at the given time. An MFD is obtained if the normal model has the highest probability which exceeds μ_T while the system has a fault. It is obviously desirable to have a higher CDID and lower FA, IFID, MFD.

4.2 Results for the numerical example

To evaluate the performance of the proposed MIMM_FDD scheme for the colored measurement noise environment, the simplified discrete-time dynamic model for the nuclear steam generator (SG) was used [15, 16]. In this model, the system and control input matrices are as follows:

$$F = \begin{bmatrix} 0.45935 & 0.10107 & 0.0294 \\ 0.37788 & 0.10037 & 0.0485 \\ 1.46789 & 0.64802 & 0.5573 \end{bmatrix} \quad (32)$$

$$G = \begin{bmatrix} 0.21232 & 0.00309 & -1.996 \\ 0.12898 & 0.00828 & -5.335 \\ 0.26252 & 0.14042 & -90.52 \end{bmatrix} \quad (33)$$

It is assumed for simplicity that all the state components are directly measurable and thus the measurement matrix H is an identity matrix and the noise gain matrix T is also an identity matrix.

In this model, input variables consist of the change in hot leg temperature, the change in feedwater temperature, and the fractional change in the main steam valve coefficient. Output variables (sensing parameters) consist of the primary fluid temperature sensor measurement, the tube temperature sensor measurement, and the steam pressure sensor measurement in the SG.

Actuator and sensor failures were modeled by multiplying the respective column of the input gain matrix G and the respective row of the measurement matrix H, respectively by a factor between zero and one, where zero corresponds to a total (or complete) actuator (or sensor) failure and one to a normal actuator (or sensor). It is assumed that the damage does not affect the system matrix F, implying that the dynamics of the system are not changed.

The following Markov transition probability matrix was used for all cases:

$$\pi = \begin{bmatrix} 0.96 & 0.02 & 0.02 \\ 0.05 & 0.95 & 0 \\ 0.05 & 0 & 0.95 \end{bmatrix} \quad (34)$$

In this simulation study, it is assumed that the correlated measurement noise is modeled as the first order AR process. The performance of the MIMM_FDD and IMM_FDD is compared for the different values of the correlation coefficient α_1. The covariance matrices for the process and measurement noise are set to the following range:

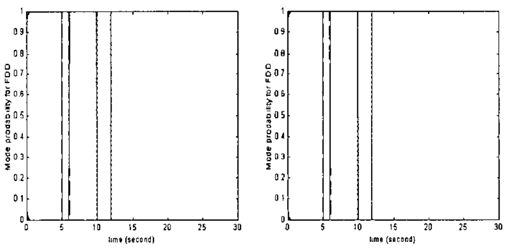
$$Q = (0.005)^2 I_3 \sim (0.002)^2 I_3,$$
$$R_{\eta_x} = (0.02)^2 I_3 \sim (0.4)^2 I_3 \quad (35)$$

For all cases, it is assumed that there are three possible modes, which consist of two failure modes and one normal mode and the sampling period $T = 0.1s$ for all the simulations.

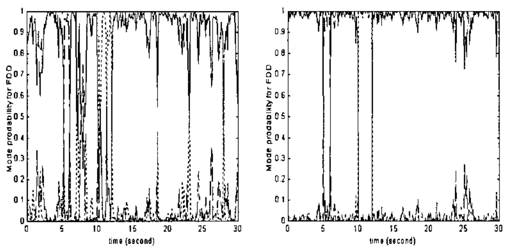
As for the faults, the following simple three cases are considered:

1) Case 1: total sensor failure

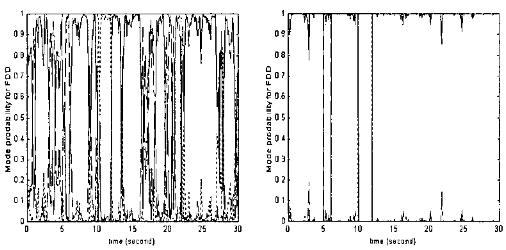
In the true dynamic model, the first and second sensors are assumed to be total failure between $k = 51$ and $k = 60$, and $k = 101$ and $k = 120$, respectively. For the remaining time interval, the normal condition holds. Fig. 2 shows the mode probabilities (μ_k) of the IMM_FDD [12] and MIMM_FDD described in this paper for the assumed scenario.



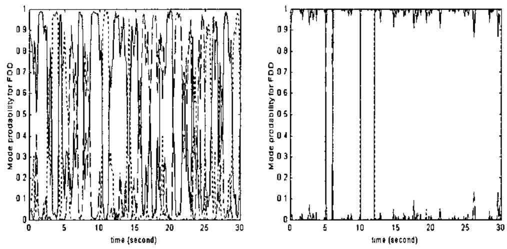
(a) IMM_FDD (α1=0.0) (b) MIMM_FDD (α1=0.0)



(c) IMM_FDD (α1=0.1) (d) MIMM_FDD (α1=0.1)



(e) IMM_FDD (α1=0.3) (f) MIMM_FDD (α1=0.3)



(g) IMM_FDD (α1=0.6) (h) MIMM_FDD (α1=0.6)

Fig. 2. Mode probabilities for total sensor failure (— : normal mode, -- : 1st sensor failure mode, ·· : 2nd sensor failure mode)

As can be seen from Figs. 2 (a) and (b), the two schemes have the same performance when $\alpha_1 = 0.0$, which corresponds to the uncorrelated case. If the value of the correlation coefficient is increased, the fault detection performance of the MIMM_FDD is improved than that of the IMM_FDD as in the Figs. 2 (c), (d), (e), (f), (g), and (h).

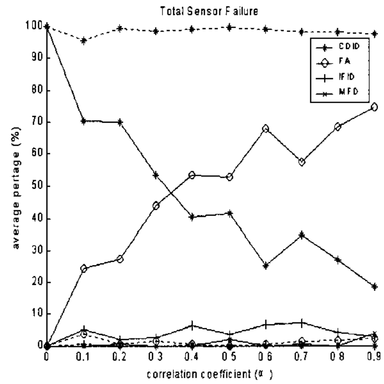
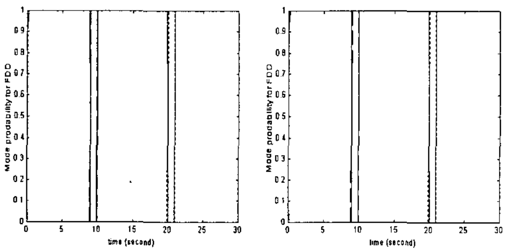


Fig. 3. Comparison of FDD results for total sensor failure (— : IMM_FDD, -- : MIMM_FDD)

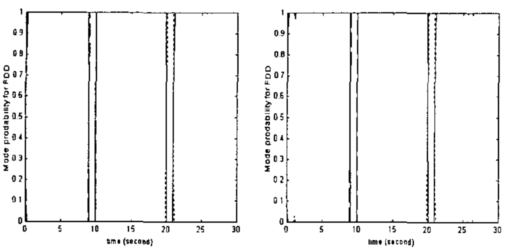
Fig. 3 presents the FDD performance indices in one cycle using the IMM and MIMM approaches. The performance indices, CDID, FA, IFID, and MFD, are presented in percentage (%) while increasing the correlation coefficient. The MIMM scheme has more enhanced performance than the IMM scheme under the colored measurement noise.

2) Case 2: total actuator failure

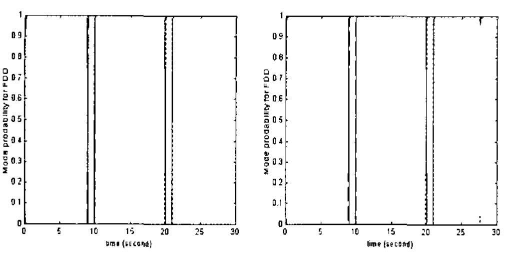
For the second case, the first and second actuators are assumed to be total failure between $k=91$ and $k=100$, and $k=201$ and $k=210$, respectively. For the remaining time interval, the normal condition holds. Fig. 4 shows the mode probabilities of the IMM_FDD and MIMM_FDD. As can be expected, the fault detection performances of the two schemes are similar since the process noise is uncorrelated.



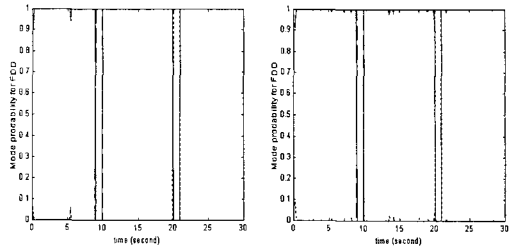
(a) IMM_FDD (α1=0.0) (b) MIMM_FDD (α1=0.0)



(c) IMM_FDD (α1=0.1) (d) MIMM_FDD (α1=0.1)



(e) IMM_FDD (α1=0.3) (f) MIMM_FDD (α1=0.3)



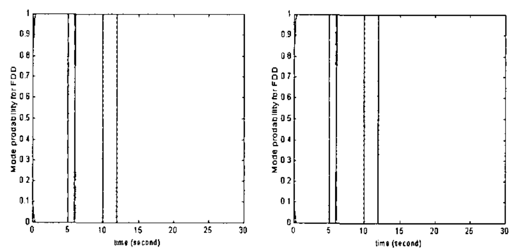
(g) IMM_FDD (α1=0.6) (h) MIMM_FDD (α1=0.6)

Fig. 4. Mode probabilities of total actuator failure (— : normal mode, -- : 1st actuator failure mode, ·· : 2nd actuator failure mode)

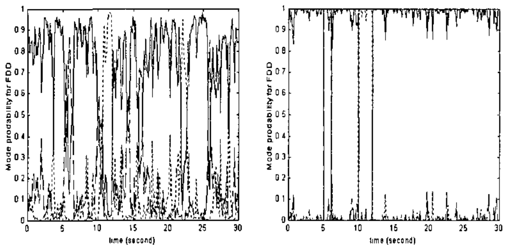
3) Case 3: partial sensor failure

In this case, the first and second sensors are assumed to be 40% partial failure between $k=51$ and $k=60$, and $k=101$ and $k=120$, respectively. For the remaining time interval, the normal condition holds. Fig. 5 shows the mode probabilities of the IMM_FDD and MIMM_FDD. Similar to the case 1 for the total sensor failure, the fault detection performance of the MIMM_FDD is enhanced significantly when the measurement noise is correlated sequentially.

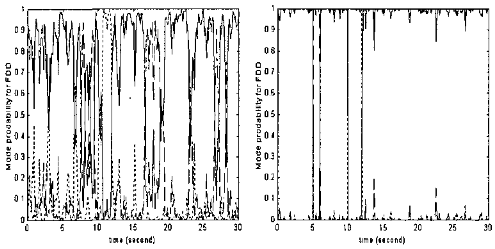
The FDD performance indices are given in Fig. 6. The MIMM scheme yields better results than the IMM scheme under the colored measurement noise.



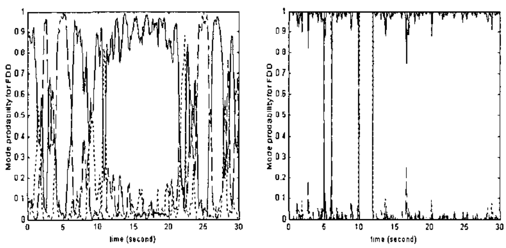
(a) IMM_FDD (α1=0.0) (b) MIMM_FDD (α1=0.0)



(c) IMM_FDD (α1=0.1) (d) MIMM_FDD (α1=0.1)



(e) IMM_FDD (α1=0.3) (f) MIMM_FDD (α1=0.3)



(g) IMM_FDD (α1=0.6) (h) MIMM_FDD (α1=0.6)

Fig. 5. Mode probabilities of partial sensor failure (— : normal mode, -- : 1st sensor failure mode, ·· : 2nd sensor failure mode)

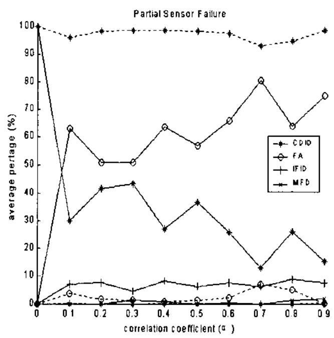


Fig. 6. Comparison of FDD results for partial sensor failure
(— : IMM_FDD, -- : MIMM_FDD)

V. Conclusion

Quite often in real situations, the measurement noise is correlated sequentially in time when the measurement frequency is high enough. In this paper, we have described an effective FDD scheme based on the modified IMM estimation algorithm.

In doing so, the correlated measurement noise is formulated as the AR model and the generalized decorrelation process is designed. The extensive computer simulation results for the nuclear steam generator model show that the proposed FDD scheme has enhanced performance when the measurement noise is correlated.

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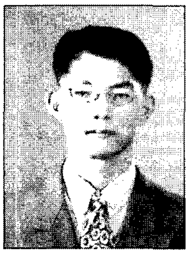

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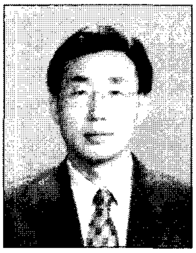

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