Detection and Diagnosis of Sensor and Actuator Failures Using IMM Estimator

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An approach to detection and diagnosis of multiple failures in a dynamic system is proposed. It is based on the interacting multiple-model (IMM) estimation algorithm, which is one of the most cost-effective adaptive estimation techniques for systems involving structural as well as parametric changes. The proposed approach provides an integrated framework for fault detection, diagnosis, and state estimation. It is able to detect and isolate multiple faults substantially more quickly and more reliably than many existing approaches. Its superiority is illustrated in two aircraft examples for single and double faults of both sensors and actuators, in the forms of "total," "partial," and simultaneous failures. Both deterministic and random fault scenarios are designed and used for testing and comparing the performance fairly. Some new performance indices are presented. The robustness of the proposed approach to the design of model transition probabilities, fault modeling errors, and the uncertainties of noise statistics are also evaluated.

Manuscript received June 24, 1997; revised January 10, 1998.

IEEE Log No. T-AES/34/4/07983.

This work was partially supported by ONR Grant N00014-97-1-0570, NSF Grants ECS-9409358 and ECS-9734285, LEQSF Grant (1996-99)-RD-A-32.

A version of this paper was presented at the 36th IEEE Conference on Decision and Control, San Diego, CA, Dec. 1997.

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I. INTRODUCTION

Modern engineering systems are becoming more and more sophisticated. The requirements for their reliability, availability, and security also grow significantly. An effective means to assure the reliability and security is to fast and reliably detect and isolate its sensor, actuator, or system component failures so that remedies may be undertaken. Towards this, many methods have been developed for fault detection and diagnosis (FDD) of dynamic systems over the last two decades [3, 7, 8, 11, 12, 30, 33].

In a modern flight control system, for example, failures of its actuator or sensor may cause serious problems and need to be detected and isolated as soon and as accurately as possible. Systems subject to such failures cannot be modeled well by a single set of equations of state that varies continuously. A more appropriate mathematical model for such a system is the so-called stochastic hybrid system. It differs from the conventional stochastic systems in that its state may jump as well as vary continuously. Apart from the applications to problems involving failures, hybrid systems have found great success in such areas as target tracking and control that involve possible structural changes [14].

One of the most effective approaches for problems that are formulated well in terms of such systems is based on the use of multiple models (MMs). It runs a bank of filters in parallel, each based on a model matching to a particular mode (i.e., structure or behavior pattern) of the system. The overall state estimate is calculated by the probabilistically weighted sum of the outputs of all filters. Since a system subject to failures is a typical hybrid system, not surprisingly, MM algorithms for FDD have been developed (see, e.g., 9, 10, 13, 27, 28, 35]) for different engineering application problems under different names, such as multiple hypothesis test detector [33], and multiple model adaptive estimation (MMAE) algorithm [24, 27]. In addition, a so-called dedicated observer scheme which uses a bank of observers for the fault detection and isolation (FDI) of deterministic systems was devised in [5] and a generalized dedicated observer to enhance the robustness of FDI was given in [7]. A neural network bank based FDI approach was developed in [39]. However, since this work deals with FDD of stochastic hybrid systems, only filter-based FDD approaches are considered. The above filter-based approaches are based on the "noninteracting" MM method originally proposed by Magill [23]: the single-model-based filters are running in parallel without mutual interaction (i.e., each filter operates independently at all times). Such an approach is quite effective in handling problems with an unknown structure or parameter but without structural or parametric changes. Clearly, the problem of FDD does not fit well into such a framework because, in general, the system structure or parameter does change as a component or subsystem fails. To compensate this weakness and to make MM algorithms fit better into the FDD, various ad hoc techniques have been proposed, such as bounded conditional probabilities [10, 25, 35], removal of β dominance effect, Kalman filter retuning, scalar penalty increase, probability smoothing, and increased residual propagation [24, 25, 27].

A notable recent advance in MM estimation is the development of the interacting multiple-model (IMM) estimator [1, 4]. It overcomes the above-mentioned weakness of the noninteracting MM approach by explicitly modeling the abrupt changes of the system by "switching" from one model to another in a probabilistic manner. Since structural changes (e.g., failures) of the system are explicitly considered and effectively handled, the IMM algorithm is much more promising for FDD. The IMM differs from the noninteracting MM algorithm in that the single-model-based filters interact each other in a highly cost-effective fashion and thus leads to significantly improved performance. It also consists of a bank of single-model-based filters running in parallel at each cycle. The initial estimate at the beginning of each cycle for each filter is a *mixture* of all most recent estimates from the single-model-based filters. It is this *mixing* that enables the IMM to effectively take into account the history of the modes (and, therefore, to yield a more fast and accurate estimate for the changed system states) without the exponentially growing requirements in computation and storage as required by the optimal estimator. On the other hand, the probability of each mode is calculated, which indicates clearly the mode in effect and the mode transition at each time. This is directly useful for the detection and diagnosis of system failures. In fact, due to its remarkable cost-effectiveness (in terms of performance versus complexity), the IMM estimator has found great success in tracking targets that may undergo a maneuver, which is a typical change in the behavior pattern of the system [1, 2]. In view of these, there is a strong hope that it will be an effective approach to FDD and thus is investigated in this work. Its main advantage over previous MM-based FDD approaches, such as MMAE, is that both single and multiple failures can be detected and identified more quickly and reliably. The effectiveness and superiority of the proposed method are demonstrated by the FDD of sensor and actuator failures of two types of high performance aircraft in this work.

After the conference version of this paper [38] was presented, the authors were brought to attention of the work reported in [6, 26] by their authors done independently around the same time, which also proposed the IMM algorithm for fault detection and identification. In [26], the IMM algorithm was used for the detection and identification of sensor and actuator failures in spacecraft autonomy. Due to the nonlinearity of the problem, extended Kalman filter was used in the IMM configuration. The IMM algorithm was used to solve a benchmark problem for detection of industrial actuator faults in [6].

The remaining of the paper is organized as follows. A description of stochastic hybrid systems and modeling of multiple failures are presented in Section II. The FDD approach based on IMM estimator is presented in Section III. Some new performance indices and design schemes for random and deterministic test scenarios are presented in Section IV. The detection and diagnosis approach for sensor and actuator failures of two types of aircraft and the performance comparison with the MMAE approaches are illustrated and discussed in Section V. Finally, conclusions are given in Section VI.

II. HYBRID SYSTEMS AND MODELING OF MULTIPLE FAILURES

A stochastic hybrid system can be described as one with both continuous-valued base state and discrete-valued structural/parametric uncertainty. A typical example of such a system is one subject to failures since fault modes are structurally different from each other and from the normal mode. An effective and natural estimation approach for such a system is the one based on MMs.

In the MM method, a set of models is assumed to represent the possible system behavior patterns or structures (system modes); a bank of filters runs in parallel at every time, each based on a particular model, to obtain model-based estimates; the overall state estimate is a certain combination of these model-based estimates; the jumps in system mode are modeled as switching/transition between the assumed models. These are the unique features of MM estimation.

A. Hybrid Dynamic Model for FDD

The MM approach to FDD assumes that the actual system at any time can be modeled sufficiently accurately by a stochastic hybrid system:

$$x(k+1) = F(k,m(k+1))x(k) + G(k,m(k+1))u(k) + T(k,m(k+1))\xi(k,m(k+1)) \tag{1}$$

$$z(k) = H(k,m(k))x(k) + \eta(k,m(k)) \tag{2}$$

(a jump-linear system is used here for simplicity) with the system mode sequence assumed to be a first-order Markov chain with transition probabilities

$$P\{m_j(k+1) \mid m_i(k)\} = \pi_{ij}(k) \qquad \forall \quad m_i, m_j \in \mathcal{S} \tag{3}$$

and

$$\sum_j \pi_{ij}(k) = 1, \qquad i = 1,\ldots,s \tag{4}$$

where $x \in R^{n_x}$ is the *base state* vector; $z \in R^{n_z}$ is the (mode-dependent) measurement vector; $u \in R^{n_u}$ is control input vector; $\xi(k) \in R^{n_\xi}$ and $\eta(k) \in R^{n_z}$ are mutually independent discrete-time process and measurement noises with mean $\bar{\xi}(k)$ and $\bar{\eta}(k)$, and covariances $Q(k)$ and $R(k)$; $P\{\cdot\}$ denotes probability; $m(k)$ is the discrete-valued *modal state* (i.e., index of the normal or fault mode) at time k, which denotes the mode in effect during the sampling period ending at t_k; π_{ij} is the transition probability from mode m_i to mode m_j; the event that m_j is in effect at time k is denoted as $m_j(k) \stackrel{\Delta}{=} \{m(k) = m_j\}$. $\mathcal{S} = \{m_1, m_2, \ldots, m_s\}$ is the set of all possible system modes; the initial state is assumed to have mean $\hat{x}_0$ and covariance P_0, and is independent of ξ and η.

The nonlinear system (1)–(2) is known as a "jump linear system:" It is linear given the system mode; however, the system may jump from one such system to another at a random time. It can be observed from (2) that the base state observations are in general noisy and mode dependent. Therefore, the mode information is imbedded (i.e., not directly measured) in the measurement sequence. In other words, the system mode sequence is an indirectly observed (or hidden) Markov chain. The transition probability matrix $\pi \stackrel{\Delta}{=} [\pi_{ij}]$ is a design parameter. Such systems can be used to model situations where the system behavior pattern undergoes sudden changes, such as system failures and target maneuver [16].

In the MM method, assume that a set of N models has been set up to approximate the hybrid system (1)–(2) by the following N pairs of equations:

$$x(k+1) = F_j(k)x(k) + G_j(k)u(k) + T_j(k)\xi_j(k) \tag{5}$$

$$z(k) = H_j(k)x(k) + \eta_j(k) \tag{6}$$

where $N \leq s$ and subscript j denotes quantities pertaining to model $m_j \in \mathcal{M}$. $\mathcal{M}$ is the set of all designed system models to represent the possible system modes in $\mathcal{S}$. System matrices F_j, G_j, T_j, and H_j may be of different structures for different j.

The FDD problem in terms of the above hybrid system is that of determining the current modal state, that is, determining whether the normal or a fault mode is currently in effect (and the current estimate of the base state) from a sequence of noisy observation.

How to design the set of models to represent the possible system modes is a key issue in the application of the MM approach, which is problem-dependent. As pointed out in [14], this design should be done such that the models (approximately) represent or cover all possible system modes at any time. This is the model set design. This design (i.e., the design of fault type, magnitude, and duration) is critical for MM-based FDD. Design of a good set of models requires a priori knowledge of the possible faults of the system.

Faults can occur in sensors, actuators, and other components of the system and may lead to failure of the whole system. They can be modeled by the abrupt changes of components of the system. Typical faults of main concern in the aircraft are sensor or actuator failures. A variety of FDD approaches have been developed for various failures [33]. In this paper, in addition to the "total" (or "hard") actuator and/or sensor failures, "partial" (or "soft") faults are also considered.

B. Hypothesized Failures

Total actuator failures may be modeled by annihilating the appropriate column(s) of the control input matrix G:

$$x(k+1) = F(k)x(k) + [G(k) + M_j]u(k) + T(k)\xi(k). \tag{7}$$

That is, choose the matrix M_j with all zero elements except that the jth column is taken to be the negative of the jth column of G. As noted in [33], the fault detection for this model is more difficult than others as the effect of the failure is modulated by the input values $u(k)$.

Alternatively, the jth actuator failure may be modeled by an additional process noise term $\varepsilon_j(k)$:

$$x(k+1) = F(k)x(k) + G(k)u(k) + T(k)\xi(k) + \varepsilon_j(k). \tag{8}$$

For total sensor failures, a similar idea can be followed. The failures can be modeled by annihilating the appropriate row(s) of the measurement matrix H described as

$$z(k) = [H(k) + L_j]x(k) + \eta(k) \tag{9}$$

or by an additional sensor noise term $e_j(k)$

$$z(k) = H(k)x(k) + \eta(k) + e_j(k). \tag{10}$$

Partial actuator (or sensor) failures are modeled by multiplying the appropriate column (or row) of G (or H) by a (scaling) factor of effectiveness. They can also be modeled by increasing the process noise covariance matrix Q or measurement noise covariance matrix R. Here we consider more complex failure situations, including total actuator and/or sensor failures, partial actuator and/or sensor failures, and simultaneous partial actuator and sensor failures. These situations require that the FDD algorithm be more responsive and robust. It is difficult for single-model-based approach to handle such complex failure scenarios.

C. Model Set Design

The fault model set design is highly dependent on the particular application considered. The major task in the application of MM estimation lies here. In general, model set design should consider both the quality and complexity of the models. Although the importance of the model set design on the performance has been hardly mentioned in the literature, it is evident in practice since the primary difficulty in applying MM estimation is to design an appropriate set of models. Unfortunately, very limited theoretical results are available on this topic [14, 18]. As pointed out in [14, 17], caution must be exercised in designing a model set. For example, there should be enough separation between models so that they are "identifiable" by the MM estimator. This separation should exhibit itself well in the measurement residuals, especially between the filters based on the matched models and those on the mismatched ones. Otherwise, the MM fault estimator will not be very selective in terms of correct FDD because it is the measurement residuals that have dominant effects on the mode probability computation which in turn affect the correctness of FDD and the accuracy of overall state estimates. In order to enhance the discrimination properties of MMAE, an interresidual distance feedback scheme was developed in [22]. On the other hand, if the separation is too large, numerical problems may occur due to ill conditions in the set of model likelihood functions.

A detailed model set design example for the FDD of actuator and/or sensor failures of two aircraft is given in Section V.

III. IMM ESTIMATOR FOR FAULT DETECTION AND DIAGNOSIS

It is well known [1] that to evaluate the minimum mean-squared error (MMSE) estimator of a system in a switching environment, the computational and storage requirements increase exponentially with time, which makes the optimal estimator *NP-complete* and thus not implementable in real time. To circumvent this problem, suboptimal estimators with certain hypothesis management, such as pruning and merging, have been used, leading to such algorithms as *generalized pseudo-Bayesian* (*GPB*) algorithm, *Detection-Estimation* algorithm, and *IMM* algorithm [1, 4].

A. MM Estimation

In the application of MM estimation techniques, the following tasks should be completed: model set design, filter selection, estimate fusion, and filter reinitialization [14]. Filter selection is to select each single-model-based recursive filter for each model, such as a Kalman filter for a linear system or an extended Kalman filter for a nonlinear system. Estimate fusion combines the model-conditional estimates to yield the overall estimate. Three approaches are available: *soft* decision, *hard* decision, and *random* decision. The reader is referred to [14] for details. How to reinitialize each single-model based filter from time to time is very important for MM estimation. Effective MM estimators distinguish among themselves primarily in this, and most research has focused here.

The simplest way of reinitialization is trivial. Each single-model-based filter uses its own previous state estimate and filter covariance as the current cycle. This leads to the so-called *noninteracting* MM estimators, referred to as MMAE in [25], because the filters are running in parallel without interactions with each other. This is the first generation of the MM estimators. Its performance may be unsatisfactory in cases in which the system mode changes because it implicitly assumes that the system mode does not change. Although this approach is not particularly suitable for problems involving structural (modal) changes, it is effective for many problems with an unknown structure/parameter and, therefore, it has been extensively used for FDD as well as many other problems [10, 13, 14, 24, 27, 35].

The second simplest way of reinitialization is to use the previous overall estimate and covariance for each filter j

$$\hat{x}_j^0(k \mid k) = E[x(k) \mid z^k] = \hat{x}(k \mid k) \tag{11}$$

$$P_j^0(k \mid k) = P(k \mid k). \tag{12}$$

This results in the first-order GPB (GPB1) estimator. Since the previous overall estimate carries information from all filters, this approach belongs to the class of *interacting* MM estimators.

A significantly better way of reinitialization is to use

$$\begin{aligned}\hat{x}_j^0(k \mid k) &= E[x(k) \mid z^k, m_j(k+1)]\\ &= E\{E[x(k) \mid m_i(k), z^k] \mid z^k, m_j(k+1)\}\\ &= \sum_i \hat{x}_i(k \mid k) P\{m_i(k) \mid z^k, m_j(k+1)\}\end{aligned} \tag{13}$$

$$\begin{aligned}P_j^0(k \mid k) &= \mathrm{cov}[\hat{x}_j^0(k \mid k)]\\ &= \sum_i P\{m_i(k) \mid z^k, m_j(k+1)\}\\ &\quad \times \{P_i(k \mid k) + \tilde{x}_{ij}^0(k \mid k)\tilde{x}_{ij}^0(k \mid k)'\}\end{aligned} \tag{14}$$

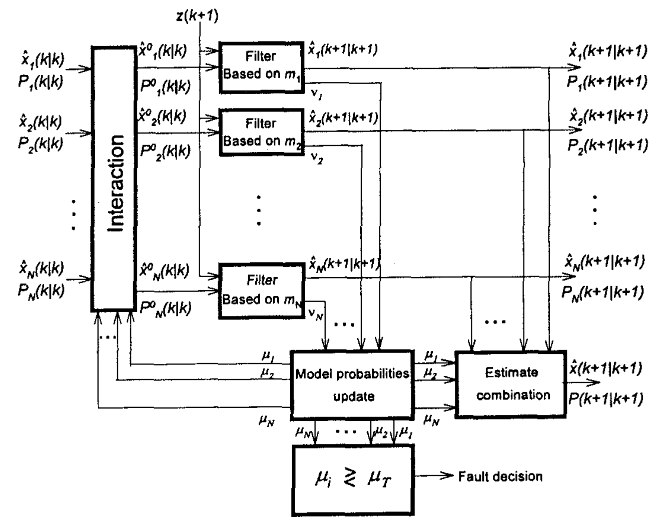

Fig. 1. Block diagram of IMM-based FDD approach.

where cov[·] stands for covariance and

$$\tilde{x}_{ij}^{0}(k \mid k) = \hat{x}_{i}^{0}(k \mid k) - \hat{x}_{j}(k \mid k). \tag{15}$$

This leads to the *IMM* estimator. Its single-model-based filters clearly interact with each other.

B. IMM Estimator

In the IMM algorithm, each filter j at time $k+1$ has its own input $\hat{x}_j^0(k \mid k)$ and $P_j^0(k \mid k)$, which form a good quasi-sufficient statistic of all old information and the assumption that model m_j matches the system mode at $k+1$. The IMM algorithm has to run each of the N filters only once in each cycle, the same as the GPB1 algorithm, and thus has computational complexity comparable to that of the GPB1 algorithm but performance close to that of the GPB2 algorithm. As a result, the IMM algorithm is generally considered to be one of the most cost-effective schemes for systems in a switching environment. It has been successfully applied to many important estimation problems compounded with structural and/or parametric changes (see [1, 2, 14] and the long lists of references therein).

The IMM algorithm is a recursive estimator. In each cycle it consists of four major steps: 1) model-conditional reinitialization (interacting 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 under the assumption that this particular mode is in effect at the present time; 2) model-conditional filtering, performed in parallel for each mode; 3) mode probability update, based on the model-conditional likelihood functions; and 4) estimate combination, which yields the overall state estimate as the probabilistically weighted sum of the updated state estimates of all filters. The probability of a mode being in effect plays a key role for determining the weights in the combination of state estimates and covariances.

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

$$\mathcal{M} = [m_1, m_2, \ldots, m_N] \tag{16}$$

where m_1 stands for the normal mode and $m_2, \ldots, m_N$ denote the possible fault modes. Then for each element in $\mathcal{M}$, we can operate a Kalman filter. The probability of each model matching to the system mode provides the required information for FDD. Fig. 1 shows the block diagram of the IMM algorithm for FDD.

Taking into account the history of the modes at k enables the IMM algorithm to yield a good estimate. In the meantime, the exponential increase in the complexity of the optimal algorithm is avoided by mixing the previous estimates at the beginning of each cycle. This is the reason for the superiority of the IMM algorithm to Magill's MM and GPB1 algorithms. For non-Gaussian noises, it was pointed out [34] that there is no performance degradation for MM estimator when the innovation ν_j is non-Gaussian for ECG/VCG (electrocardiography/vectorcardiography) rhythm diagnosis [10] and detection of incidents on highways [35]. This means that the MM algorithm can be expected to be reasonably robust to non-Gaussian statistics. This observation should be applicable to the IMM approach also.

C. Fault Detection and Diagnosis Scheme

The model probabilities provide an indication of mode in effect at any time. It is natural to be used as

TABLE I
One Cycle of IMM-Based FDD Scheme

1. Interaction/Mixing of the estimates (for $j = 1, 2, ..., N$):

   predicted mode probability: $\mu_j(k+1|k) \triangleq P\{m_j(k+1)|z^k\} = \sum_i \pi_{ij}\mu_i(k)$

   mixing probability: $\mu_{i|j}(k) \triangleq P\{m_i(k)|m_j(k+1), z^k\} = \pi_{ij}\mu_i(k)/\mu_j(k+1|k)$

   mixing estimate: $\hat{x}_j^0(k|k) \triangleq E[x(k)|m_j(k+1), z^k] = \sum_i \hat{x}_i(k|k)\mu_{i|j}(k)$

   mixing covariance: $P_j^0(k|k) \triangleq \mathrm{cov}[\hat{x}_j^0(k|k)|m_j(k+1), z^k]$

   $$= \sum_i \left[P_i(k|k) + [\hat{x}_j^0(k|k) - \hat{x}_i(k|k)][\hat{x}_j^0(k|k) - \hat{x}_i(k|k)]'\right]\mu_{i|j}(k)$$

2. Model-conditional filtering (for $j = 1, 2, ..., N$):

   predicted state (from k to $k+1$):

   $$\hat{x}_j(k+1|k) \triangleq E[x(k+1)|m_j(k+1), z^k] = F_j(k)\hat{x}_j^0(k|k) + G_j(k)u(k) + T_j(k)\bar{\xi}_j(k)$$

   predicted covariance:

   $$P_j(k+1|k) \triangleq \mathrm{cov}[\hat{x}_j(k+1|k)|m_j(k+1), z^k] = F_j(k)P_j^0(k|k)F_j(k)' + T_j(k)Q_j(k)T_j(k)'$$

   measurement residual: $\nu_j \triangleq z(k+1) - E[z(k+1)|m_j(k+1), z^k]$

   $$= z(k+1) - H_j(k+1)\hat{x}_j(k+1|k) - \bar{\eta}_j(k+1)$$

   residual covariance: $S_j \triangleq \mathrm{cov}[\nu_j|m_j(k+1), z^k] = H_j(k+1)P_j(k+1|k)H_j(k+1)' + R_j(k+1)$

   filter gain: $K_j = P_j(k+1|k)H_j(k+1)'S_j(k+1)^{-1}$

   updated state: $\hat{x}_j(k+1|k+1) \triangleq E[x(k+1)|m_j(k+1), z^{k+1}] = \hat{x}_j(k+1|k) + K_j\nu_j$

   updated covariance:

   $$P_j(k+1|k+1) \triangleq \mathrm{cov}[\hat{x}_j(k+1|k+1)|m_j(k+1), z^{k+1}] = P_j(k+1|k) - K_j(k+1)S_j(k+1)K_j(k+1)'$$

3. Mode probability update and FDD logic (for $j = 1, 2, ..., N$):

   likelihood function: $L_j(k+1) = \mathcal{N}[\nu_j(k+1); 0, S_j(k+1)]$

   $$= \frac{1}{\sqrt{|(2\pi)S_j(k+1)|}}\exp\left[-\frac{1}{2}\nu_j(k+1)'S_j^{-1}(k+1)\nu_j(k+1)\right]$$

   mode probability: $\mu_j(k+1) \triangleq P\{m_j(k+1)|z^{k+1}] = \frac{\mu_j(k+1|k)L_j(k+1)}{\sum_i \mu_i(k+1|k)L_i(k+1)}$

   fault decision: $\mu_j(k+1) = \max_i \mu_i(k+1) \begin{cases} > \mu_T \Rightarrow H_j : \text{fault } j \text{ occurred} \\ < \mu_T \Rightarrow H_1 : \text{no fault} \end{cases}$

4. Combination of estimates (no need unless integrated with state estimation):

   overall estimate: $\hat{x}(k+1|k+1) \triangleq E[x(k+1)|z^{k+1}] = \sum_j \hat{x}_j(k+1|k+1)\mu_j(k+1)$

   overall covariance:

   $$P(k+1|k+1) \triangleq E\left[[x(k+1) - \hat{x}(k+1|k+1)][x(k+1) - \hat{x}(k+1|k+1)]'|z^{k+1}\right]$$

   $$= \sum_j [P_j(k+1|k+1) + [\hat{x}(k+1|k+1) - \hat{x}_j(k+1|k+1)][\hat{x}(k+1|k+1) - \hat{x}_j(k+1|k+1)]']\mu_j(k+1)$$

an indication of a failure. By using the information provided by the model probabilities, both fault detection and diagnosis can be achieved. The fault decision can be made by

$$\mu_j(k+1) = \max_i \mu_i(k+1)$$
$$\begin{cases} > \mu_T \Rightarrow H_j : \text{fault } j \text{ occurred} \\ < \mu_T \Rightarrow H_1 : \text{no fault} \end{cases} \tag{17}$$

A slightly better logic is

$$\mu_j(k+1) = \max_i \mu_i(k+1),$$
$$\frac{\mu_j(k+1)}{\max_{i \neq j}\mu_i(k+1)} \begin{cases} > \mu_T' \Rightarrow H_j : \text{fault } j \text{ occurred} \\ < \mu_T' \Rightarrow H_1 : \text{no fault} \end{cases} \tag{18}$$

A complete cycle of the IMM-based FDD scheme with Kalman filters as its mode-matched filters is summarized in Table I.

The IMM approach to FDD offers a number of important advantages over other approaches, such as the SPRT and generalized likelihood ratio (GLR) approaches. It is also superior to the Magill's MM approach, its variants, and the GPB1 approaches.

1) Note that decision rule (17) provides not only fault detection but also the information of the type (sensor or actuator), location (which sensor or actuator), size (total failure or partial fault with the fault magnitude) and fault occurrence time, that is, simultaneous detection and diagnosis. For partial faults, the magnitude (size) can be determined by the probabilistically weighted sum of the fault magnitudes of the corresponding partial fault models. Another advantage of the IMM approach is that FDD is integrated with state estimation. The overall estimate provides the best state estimation of the system subject to failures. Furthermore, unlike other observer-based or Kalman filter based approaches, there is no extra computation for the fault decision because the model probabilities are necessary in the IMM algorithm anyway.

2) For a reliable fault decision by using some other single-model-based fault detection approaches, such as the chi-square test and GLR techniques, the residual window length and the decision threshold must be chosen to have a trade-off for detection performance and computational simplicity. In contrast, in the IMM approach, the set of model probabilities $\{\mu_j(k+1)\}$, unlike the set of likelihoods $\{L_j(k+1)\}$, summarizes all the previous and current information about the system modes in effect and thus is more reliable for a fault decision. A sliding-window for fault decision is not necessary. For a more robust decision, additional information from the likelihoods and/or residuals may be used. Note, however, that their values depend heavily on the current measurements which carry unreliable information about the system mode in effect.

3) For the proposed IMM approach, there is no need to set arbitrary threshold levels to balance false alarms against missed detections. However, it is convenient to detect a possible failure by setting a threshold μ_T, as in (17) and (18). One can easily determine the detection threshold μ_T. This simplicity will prove to be attractive in practice.

4) It is well-known that for the noninteracting MM estimators, if one of the model probabilities becomes very large (close to unity), the others usually do not increase quickly enough when a fault (mode change) occurs. In addition, a too large separation (or difference) between models may lead to numerical underflow in the computation of the likelihood function. Therefore, an artificial lower bound $\mu_{\min}$ is imposed on the model probabilities of these MM estimators, with the constraint that the sum of all the probabilities is 1. This has an obvious disadvantage that different $\mu_{\min}$ may have different impact on the FDD performance, which is relevant to the size of model set and the application considered. It means that we have to tune carefully for each application. In contrast, it is not necessary for the IMM algorithm to have such a lower bound in its mode probability because the assumption that a mode may jump to another alleviates this problem.

5) The gains in the Kalman filters based on the mismatched models decrease monotonically with time. Thus even if a lower bound on the probabilities is set, an abrupt fault may not be reflected in a corresponding change in the filter estimates timely. In order to overcome this difficulty, a resetting (reinitialization) technique was adopted in [10] which resets both the filter parameters and the probabilities to their initial values when a fault has been detected, and thus all the previous information is lost. Another problem is that it takes time for the reinitialized filter to lock onto the new mode which, in turn, may lead to the detection delay or missed detection for subsequent failures. However, these difficulties are effectively and automatically overcome by the IMM algorithm due to the interaction/mixing of previous estimates. The probabilities, estimates as well as the associated covariance are reinitialized in a near optimal way in the IMM approach where most of previous information is included in the current initial probabilities and estimates. This leads to a significant improvement in performance.

6) It is worth pointing out that in the IMM approach, the overall estimate is generated by the probabilistically weighted sum of estimates from the single-model-based filters. It is better and more robust than any single-model-based estimate. This state estimate does not depend upon the correctness of fault detection and in fact, the accurate state estimation can facilitate the correct FDD.

7) The detection threshold μ_T is universal in the sense that it does not depend much on the particular problem at hand and a robust threshold can be determined easily. In other words, the FDD performance of the IMM approach varies little in most cases with respect to the choice of this threshold. In addition, the model probabilities in the IMM approach provide a meaningful measure of how likely each fault mode is without the need to compare with the threshold μ_T. This measure is known and independent of the threshold used for the declaration of a fault and the use of a threshold is not essential, but mainly for convenience. On the other hand, the residual-based fault detection logic relies heavily on the threshold used, which is problem-relevant. Quite different detection thresholds have to be used for FDD problems of different systems and design of such a threshold is not trivial. Moreover, without comparing with the threshold, the value of the measurement residual itself does not provide directly meaningful detection and indication of the fault situations.

8) The IMM approach can be readily extended to MM-based fault-tolerant control and provides extremely useful information for system compensation or fault-tolerant control subsequent to the detection of a failure, similarly to what was done in [25, 29]. The main idea is that the overall control can be generated by the probabilistically weighted sum of single-model-based controls. This work is under investigation and will be reported in the future.

Compared with the MMAE approach, the disadvantages of the proposed IMM approach are a higher computational complexity and the need to design the mode transition probabilities. These advantages and disadvantages are demonstrated via simulation in Section V.

D. Design of the Markov Transition Probability Matrix

The design parameters for the IMM algorithm include the transition probability matrix, the covariances of the process noise and measurement noise. Note that the performance of FDD depends also on the type and magnitude of control input excitation used. However, the design of the transition probability matrix is unique and important for the IMM-based FDD approach.

A proper choice of the diagonal entries in the transition probability matrix is to match roughly the mean sojourn time of each mode [2],

$$\pi_{jj} = \max\left\{ l_j, 1 - \frac{T}{\tau_j} \right\} \tag{19}$$

where τ_j is the expected sojourn time of the jth mode; π_{jj} is the probability of transition from jth mode to itself and T is the sampling interval; l_j is a designed lower limit for the jth model transition probability. For example, the "normal-to-normal" transition probability, π_{11}, can be obtained by $\pi_{11} = 1 - T/\tau_1$, where τ_1 denotes the mean time between failures (MTBF). Note that T is much smaller than MTBF in practice.

The transition probability from the normal mode to a fault mode is equal to $1 - \pi_{11}$. Which particular fault mode it jumps to depends on the relative likelihood of the occurrence of the fault mode. While in reality mean sojourn time of total failures is the down time of the system, which is usually large and problem-dependent, to incorporate various fault modes into one sequence for a convenient comparison of different FDD approaches, the sojourn time of the total failures is assumed to be the same as that of the partial faults in this work.

"Fault-to-fault" transitions are normally disallowed except in the case where there is sufficient prior knowledge to believe that partial faults can occur one after another.

E. Numerically Robust Implementation of IMM and MMAE Estimation Algorithms

As explained in Section IIIB, it is not necessary for the IMM algorithm to have a lower bound on its model probabilities. However, numerical underflow may occur if the model difference is too large. Simple solutions are to replace the zero model transition probabilities with an extremely small value, say, 10^{-300}, or set a low bound for model probabilities. However, these are ad hoc. A more general and numerically robust implementation of the MMAE and IMM algorithms was developed in [19], where the need for a lower bound is eliminated. In order to compare the effectiveness of the numerically robust implementation with the commonly used MMAE algorithm, an artificial lower bound ($\mu_{\min} = 0.001$ in our simulation, $\mu_{\min} = 0.01$ in [32, 35] and $\mu_{\min} = 0.001$ in [22, 27]) was imposed on the MMAE algorithm (MMAE2).

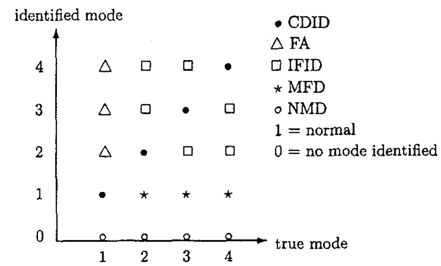

Fig. 2. Description of FDD performance indices.

IV. FDD PERFORMANCE EVALUATION AND DESIGN OF TEST SCENARIOS

A. Performance Evaluation and Indices

In order to evaluate the FDD performance of different MM estimators, in addition to the conventional performance indices, such as the false alarm (FA) and missed fault detection (MFD), the following performance indices were designed and used in this work: average percentages of correct detection and identification (denoted by CDID), incorrect fault identification (denoted by IFID), no mode detection (denoted by NMD), and average detection delay. 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 indecisive (NMD) if no model has a probability above μ_T. The detection and correct identification delay is obtained from the time the true mode changes to the time it is detected and correctly identified. It is obviously desirable to have a higher CDID and lower FA, IFID, MFD, and NMD. Fig. 2 depicts the relationship among different performance indices, where 0th identified mode means no model has probability larger than μ_T. The new indices were adopted and modified from [18].

The performance indices given above should not be applied to different model set designs; otherwise they may be misleading: the more models, the worse the performance. In order to overcome this limitation, the computation of above CDID, FA, IFID, MFD, and NMD are obtained based on the fault models corresponding to each sensor (or actuator) instead of each fault mode. In addition, average distance between the system mode in effect at a given time k and the models used in an MM algorithm at that time was introduced in [18] and used in this work:

$$\text{Distance} = \frac{1}{N_{\text{run}}}\sum_{n=1}^{N_{\text{run}}} \times \left\{ \frac{1}{k_{\max}} \sum_{k=1}^{k_{\max}} \left\{ \sum_{m_i \in \mathcal{N}_s} \|s_k - m_i\| P\{s_k = m_i \mid s_k \in \mathcal{N}_s, z^k\} \right\} \right\} \tag{20}$$

where $\mathcal{N}_s$ represents the model set consisting of the partial and total fault models pertaining to a given sensor (or actuator); $\|s_k - m_i\|$ is the distance between the true mode and model m_i in model set $\mathcal{N}_s$; and N_{run} is the number of Monte Carlo runs. With these performance indices, more reasonable and fair FDD performance evaluation can be obtained.

B. Design of Test Scenarios

The FDD performance depends to some degree on the test scenarios used. In order to evaluate the performance of different FDD algorithms more fairly and precisely, both deterministic and random fault scenarios were designed. These designs, especially the random scenario, are useful not only for MM-based approaches. Different failure types, such as total/partial sensor and/or actuator failures, single or double actuator and/or sensor failures were simulated.

1) *Random Scenario*: For the random scenario, it is assumed that the system mode sequence is a semi-Markov process, that is, a process that would be Markov were the sojourn time τ for each mode not random. Total and partial faults with a random magnitude uniformly distributed over $(0,1]$ were designed. It implies that the dynamic system undergoes jumps from the normal mode to a fault mode with a magnitude of either 1 (total fault) or the value uniformly distributed over $(0,1]$ (partial fault) after staying in the normal mode for a random period of time τ. It is assumed that a fault mode can switch only to the normal mode. Which sensor/actuator undergoes the fault is also assumed random that is evenly distributed among sensors/actuators. The following designs of the sojourn time τ, fault magnitude f, and the indication λ of the mode are proposed.

a) The sojourn time τ_i for the fault $f = f_i$ has the conditional probability density

$$p(\tau_i \mid f_i) = \mathcal{N}(\tau_i; \overline{\tau}_i, \sigma^2_{\tau_i}) \qquad \tau_i > 0 \tag{21}$$

where $\mathcal{N}(\tau_i; \overline{\tau}_i, \sigma^2_{\tau_i})$ stands for Gaussian (normal) probability density function of τ_i with mean $\overline{\tau}_i$ and variance $\sigma^2_{\tau_i}$; and $\overline{\tau}_i$ and $\sigma^2_{\tau_i}$ are two constants, depending on the fault magnitude f_i.

b) The magnitude f_{i+1} of a fault over the random period $(t_i, t_{i+1}]$ has the conditional probability density

$$p(f_{i+1} \mid f_i = 0) = P^0 \delta(f_{i+1} - f_M) + (1 - P^0)\frac{1}{f_M} 1[f_{i+1}; (0, f_M)] \tag{22}$$

$$p(f_{i+1} = 0 \mid f_i \neq 0) = 1 \tag{23}$$

where δ is the delta function; $1[x;S]$ is the indicator function, defined by

$$1[x;S] = \begin{cases} 1 & x \in S \\ 0 & x \notin S \end{cases}. \tag{24}$$

c) The indicator λ_{i+1} of a fault sensor (actuator) over the random period $(t_i, t_{i+1}]$ has the conditional probability mass function

$$P\{\lambda_{i+1} = j \mid \lambda_i = 1, 2 < j < \dim(y) + 1\} = \frac{1}{\dim(y)} \tag{25}$$

i.e., λ_{i+1} (conditioned on $\lambda_i = 1$) is evenly distributed over $\{2, \ldots, \dim(y) + 1\}$, and

$$P\{\lambda_{i+1} = 1 \mid \lambda_i \neq 1\} = 1 \tag{26}$$

where $\dim(y)$ stands for the dimension of vector y which corresponds to the number of sensors or actuators and $\lambda = 1$ denotes the normal mode.

The following parameters were used in the design of our random scenario:

$$\begin{aligned} \overline{\tau}_i &= \overline{\tau}_M + \frac{f_M - f_i}{f_M}(\overline{\tau}_0 - \overline{\tau}_M), \\ \sigma^2_{\tau_i} &= \tfrac{1}{12}\overline{\tau}_i, \\ \overline{\tau}_0 &= \tau_{\text{normal}}/T, \\ \overline{\tau}_M &= \tau_{\text{fault}}/T, \\ P^0 &= 0.4, \\ f_M &= 1 \end{aligned} \tag{27}$$

where $\tau_{\text{normal}} = 3$ and $\tau_{\text{fault}} = 1$ stand for the expected sojourn time for normal and fault mode, respectively. P^0 represents the probability of a total failure.

This random scenario design was modified from [21] for maneuvering target tracking. With such a random scenario, it is difficult to design an algorithm with subtle tricks that are effective only for certain scenarios.

2) *Deterministic Scenarios*: Several deterministic test scenarios were also designed. The design rule follows the sequence from simpler to more complex fault cases to represent possible actual failures in the aircraft sensors and actuators. The details are given in Section V.

Note that our deterministic scenarios have more frequent mode changes than in most practical situations. With so frequent mode changes, many different fault modes are incorporated into one sequence so that it is more convenient for the comparison of different FDD approaches. Such scenarios also allow us to consider situations of intermittent faults.

V. DETECTION AND DIAGNOSIS OF AIRCRAFT SENSOR AND ACTUATOR FAILURES

A. Aircraft Model and Model Set Design

Two types of aircraft were used for the detection and diagnosis of sensor and actuator failures. The dynamics of an F/A-18 aircraft [31] in a given region of the flight envelope, level flight at 10,000 ft with a speed of Mach 0.6, and another high performance aircraft [29] with a high subsonic cruise speed (Mach = 0.8) at an altitude of 35,000 ft, can be linearized and their motion can be described by the continuous-time state variable equations

$$\dot{x}(t) = Ax(t) + BU(t) + \xi_c(t) \tag{28}$$

$$z(t) = Cx(t) + \eta(t). \tag{29}$$

For F/A-18 aircraft, the model has eight (four longitudinal and four lateral) state variables with the longitudinal and lateral motions completely decoupled. It is represented by state vector $x = [u\ w\ q\ \theta\ v\ r\ p\ \varphi]'$, where u,v,w represent velocities in forward, lateral, and vertical directions of the body axes, respectively; p,q,r represent roll, pitch, and yaw angular rates, respectively; θ, φ are pitch and roll angles, respectively. The aircraft utilizes five pairs of control surfaces (some of which can be used symmetrically and asymmetrically) to achieve seven different control inputs, represented by $U = [\delta_e\ \delta_{\rm sle}\ \delta_{\rm ste}\ \delta_{\rm ast}\ \delta_{\rm ate}\ \delta_a\ \delta_r]'$. The seven control input variables, three for longitudinal control and four for lateral control, are symmetric stabilator (or elevator denoted by δ_e), symmetric leading edge flap ($\delta_{\rm sle}$), symmetric trailing edge flap ($\delta_{\rm ste}$), asymmetric stabilator ($\delta_{\rm ast}$), asymmetric trailing edge flap ($\delta_{\rm ate}$), aileron (δ_a) and rudder (δ_r). A and B, given in Appendix A, represent the system and control matrices at the given normal flight condition, respectively. A more detailed description of the F/A-18 aircraft can be found in [31].

For the second aircraft, the model has eight (four longitudinal and four lateral) state variables, with the longitudinal and lateral motions completely decoupled, represented by state vector $x = [\alpha\ q\ u\ \theta\ \beta\ p\ r\ \varphi]'$, where u represents forward velocity; p,q,r represent roll, pitch, and yaw angular rates, respectively; α,β denote angle of attack and angle of sideslip, respectively; θ, φ are pitch and roll angles, respectively. The control input vector is represented by $U = [\delta_{\rm EL}\ \delta_{\rm ER}\ \delta_{\rm CL}\ \delta_{\rm CR}\ \delta_{\rm SL}\ \delta_{\rm SR}\ \delta_A\ \delta_R]'$. They are left and right elevators (denoted by $\delta_{\rm EL}$ and $\delta_{\rm ER}$), left and right canards ($\delta_{\rm CL}$ and $\delta_{\rm CR}$), left and right spoilers ($\delta_{\rm SL}$ and $\delta_{\rm SR}$), aileron (δ_A), and rudder (δ_R). Only two control inputs, left elevator $\delta_{\rm EL}$ and right elevator $\delta_{\rm ER}$, are relevant to the longitudinal movement of the aircraft under the normal flight condition. Only FDD of sensor and actuator failures of the longitudinal dynamics was considered in this testing example due to the limitation in space. A more detailed description of the aircraft can be found in [29]. The system and control matrix A,B are given in Appendix B.

Discretization of (28)–(29) yields

$$x(k+1) = Fx(k) + GU(k) + \xi(k) \tag{30}$$

$$z(k) = Hx(k) + \eta(k) \tag{31}$$

where sampling period $T = 0.1$ s, $F = e^{AT}$; $G = (\int_0^T e^{A\tau}\,d\tau)B$; $H = C$.

It was assumed for simplicity that all the state components are directly measurable and thus H (or C) is an identity matrix.

Actuator (or control surface) failures were modeled by multiplying the respective column of G matrix by a factor between zero and one, where zero corresponds to a total (or complete) actuator failure or missing control surface and one to an unimpaired (normal) actuator/control surface. Likewise for sensor failures, where the role of G is replaced with H. It was assumed that the damage does not affect the aircraft's F matrix, implying that the dynamics of the aircraft are not changed. We could also assume that F matrix undergoes changes due to the failure of actuator or component of the aircraft. This is related to the model design for the MM approach and is not considered here.

The fault modes in this work are more general and complex than those considered before, including total single sensor or actuator failures, partial single sensor or actuator failures, total and partial single sensor and/or actuator failures, and simultaneous sensor and actuator failures. Generally speaking, it is difficult to handle simultaneous faults, e.g., simultaneous actuator and sensor faults, even though the failure scenarios which included dual faults separated by 3.0, 0.5, and 0.1 s were considered in [27]. Here, the simultaneous actuator and sensor faults are considered.

If failures with different fault magnitudes need to be detected and diagnosed, variable-structure IMM estimators, as proposed in [17, 20, 21], can also be used to reduce the computational complexity of the FDD algorithm, where different models may assume different failure magnitudes. Another way to reduce the computational requirement is to use the hierarchical structure of the fault model set [27, 32]. Such techniques are not exploited here because the purpose of this work is to develop a generic FDD algorithm and compare it with existing MM-based FDD algorithms.

B. Robustness to the Design of Transition Probabilities, Modeling Errors, and Noise Statistics

A major difference between the proposed approach and other MM-based approaches is the assumption of Markov process for the system failures. An issue related to this assumption is how robust the proposed approach is to the design of the model transition probability matrix. Applications of the IMM algorithm to the target tracking indicated that the performance of the IMM algorithm is not sensitive to the choice of the transition probabilities [14, 16]. This characteristic is also valid for FDD. This robustness is evaluated and compared with other MM-based FDD approaches via simulations.

Other robustness issues with respect to modeling errors or errors in noise statistics are also important to the application of the proposed approach. The greater the errors are, the more serious the degradation of the FDD performance is. A good FDD approach should be robust (insensitive) to such errors. In order to evaluate the robustness, modeling errors of different magnitudes and uncertainties in noise statistics were simulated. Several deterministic and random test scenarios were used to evaluate the robustness of the proposed approach. Only results for Scenario 3 (deterministic) and Scenario 4 (random) are reported, to save space.

C. FDD Results for F/A-18 Aircraft

It is assumed for simplicity in our simulation that the sojourn time is $\tau_{\text{normal}} = 3$ s and $\tau_{\text{fault}} = 1$ s for normal flight condition and a sensor and/or actuator failure, respectively, although it is more reasonable to assume different sojourn times for different sensor and actuator failures. The following transition probability matrix was used for scenario 1 below:

$$\pi = \begin{bmatrix} \frac{116}{120} & \frac{1}{120} & \frac{1}{120} & \frac{1}{120} & \frac{1}{120} \\ 0.05 & 0.95 & 0.0 & 0.0 & 0.0 \\ 0.05 & 0.0 & 0.95 & 0.0 & 0.0 \\ 0.05 & 0.0 & 0.0 & 0.95 & 0.0 \\ 0.05 & 0.0 & 0.0 & 0.0 & 0.95 \end{bmatrix}.$$

Similar transition probability matrices were used for the other scenarios. The system and measurement noise matrices used for all scenarios were

$$Q = (0.01)^2 I, \qquad R = (0.2)^2 I.$$

In the case where there is no *a priori* information about the system model in effect, it is natural to set the initial model probabilities to be equal (but the normal mode may have a higher initial probability).

1) *FDD Results of Longitudinal Dynamics*:

Scenario 1. Single total/partial sensor/actuator failure: First, consider the simplest situation in which only a single total (or partial) sensor or actuator failure is possible. Then there are a total of 5 possible models (4 failure plus one normal models) for sensor failures and 4 possible models (3 failure plus one normal models) for actuator failures. Similarly, there are 5 partial sensor failure models and 4 partial actuator failure models. Due to the space limitation, only the simulation result for the first case is presented herein.

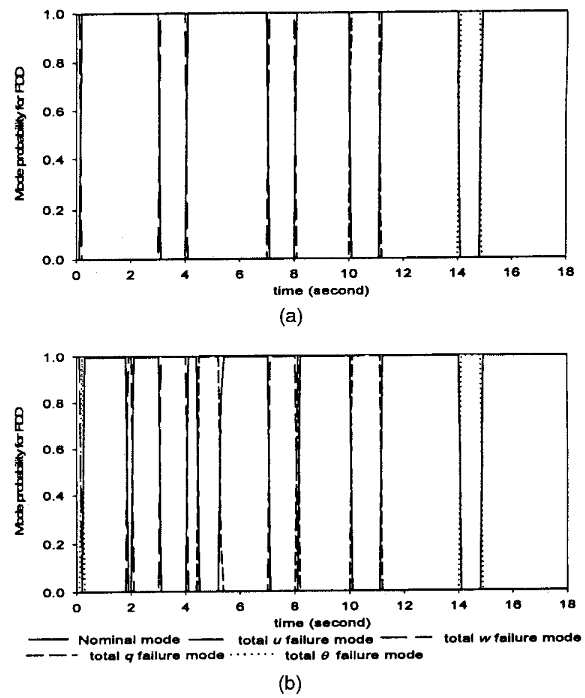

Fig. 3. Comparison of mode probabilities of single total sensor failures. (a) IMM. (b) MMAE.

Fig. 3 shows the mode probabilities when there is a total forward velocity (u) failure between $k = 31$ and $k = 40$, a vertical velocity (w) failure between $k = 71$ and 80, a total pitch rate (q) failure between $k = 101$ and $k = 111$, and a total pitch angle (θ) failure between $k = 141$ and 148. For the remaining time, the normal flight condition holds. Note that sampling period $T = 0.1$ s.

Table II presents the FDD performance indices and the flops (in 10^4) in one cycle using the IMM and MMAE approaches, with a MATLAB implementation. IMM represents a numerically robust IMM algorithm implementation. MMAE1 represents a numerically robust MMAE algorithm implementation. MMAE2 represents the MMAE algorithm with 10^{-3} lower bound for each mode probability. Case 1 represents the situation in which the model set and the noise statistics are known exactly. The FDD results for this case were demonstrated in Fig. 3 and the subsequent figures. Case 2 differs from Case 1 in that a 5% modeling error exists. In Case 3, the noise matrices Q and R used for the filter are 4 times the true ones so

TABLE II
Comparison of FDD Results for Single Total Sensor Failures

		CDID	FA	IFID	MFD	NMD	Delay	Flops
Case 1	IMM	95.56	4.44	0	0	0	0	1.392
	MMAE1	35.56	46.11	12.78	5.55	0	0	1.158
	MMAE2	92.67	7.33	0	0	0	0	1.159
Case 2	IMM	88.89	6.11	1.11	3.89	0	0	1.392
	MMAE1	35.56	46.11	12.78	5.55	0	0	1.158
	MMAE2	88.33	7.22	3.33	1.11	0	0.1	1.159
Case 3	IMM	95.56	4.44	0	0	0	0	1.392
	MMAE1	35.56	46.11	12.78	5.55	0	0	1.158
	MMAE2	92.58	7.35	0	0	0.07	0.1	1.159

TABLE III
FDD Results for Single Total and Partial Sensor and/or Actuator Failures

		CDID	FA	IFID	MFD	NMD	Delay	Flops
Case 1	IMM	82.00	9.00	9.00	0	0	0	3.684
	MMAE1	60.50	15.00	24.5	0	0	1.1	2.567
	MMAE2	80.76	10.24	9.00	0	0	0	2.581
Case 2	IMM	82.00	9.00	9.00	0	0	0	3.684
	MMAE1	61.45	14.05	1.80	22.7	0	0.91	2.567
	MMAE2	80.76	10.24	9.00	0	0	0	2.581
Case 3	IMM	82.00	9.00	9.00	0	0	0	3.684
	MMAE1	61.00	14.50	2.00	22.5	0	1.1	2.567
	MMAE2	80.75	10.22	9.00	0	0.03	0.001	2.581

that the performance impact due to the uncertainties in noise statistics can be evaluated. Cases with other different modeling errors and uncertainties in noise statistics were also simulated. The results are averages over 100 Monte Carlo simulations. The performance indices, CDID, FA, IFID, MFD, and NMD, are presented in percentage (%).

Scenario 2. Total and partial sensor and/or actuator failures: In order to reduce the computation and the size of model set, only symmetric stabilator (δ_e) fault was considered for actuator failures. A total of 11 models (one normal mode, four total sensor failure, four 40% partial sensor failure, one total actuator failure, and one 40% partial actuator failure models) were used. Fig. 4 shows the mode probabilities when there is a total pitch rate (q) failure between $k = 31$ and $k = 40$, a total pitch angle (θ) failure between $k = 71$ and 80, a 40% partial symmetric stabilator failure between $k = 101$ and $k = 111$, a total symmetric stabilator failure between $k = 141$ and $k = 149$, and a 40% partial pitch angle failure between $k = 176$ and $k = 185$. The FDD performance indices and the flops are given in Table III. The IMM algorithm yielded better results than the MMAE algorithm. MMAE1 obtained worst results again. It is worth pointing out that better performance may be obtained by the IMM algorithm with lower bound on transition probability matrix or model probabilities.

Scenario 3. Total and partial sensor/actuator failures, simultaneous partial sensor and actuator failures: In this situation, more complicated failures, including simultaneous sensor and actuator failures, were considered. In order to reduce the computation and the size of model set, only symmetric stabilator fault was considered for actuator failures also. This leads to a total of 15 models in the model set: one normal, four total sensor failure, four 40% partial sensor failure, one total actuator failure, one 40% partial actuator failure, and four simultaneous sensor and actuator failure models. Fig. 5 shows the mode probabilities when there is a total pitch rate failure between $k = 31$ and $k = 40$, a simultaneous 20% partial pitch rate and symmetric stabilator failures between $k = 71$ and 80, a 40% partial symmetric stabilator failure between $k = 101$ and $k = 111$, a 40% partial pitch angle failure between $k = 141$ and $k = 149$; and a total symmetric stabilator failure between $k = 176$ and $k = 185$. The FDD results are given in Table IV. Better results were obtained by the IMM algorithm than by the MMAE algorithm.

Scenario 4. Random scenarios with total and partial actuator/sensor failures: In this scenario, actuator or sensor failures with total and partial faults were designed separately. In the random test scenario, the magnitude of a partial fault was designed as uniformly distributed over $(0, 1)$. It is important to design the model set that covers the fault situation

TABLE IV
FDD Results for Single Total and Partial Sensor and/or Actuator Failures

		CDID	FA	IFID	MFD	NMD	Delay	Flops
Case 1	IMM	91.00	9.00	0	0	0	0	5.588
	MMAE1	66.00	9.50	0	24.5	0	0	3.518
	MMAE2	88.80	10.27	0.5	0	0.43	0.182	3.549
Case 2	IMM	91.00	9.00	0	0	0	0	5.588
	MMAE1	66.00	9.50	0	24.5	0	0	3.518
	MMAE2	88.98	10.26	0.5	0	0.26	0.149	3.549
Case 3	IMM	91.00	9.00	0	0	0	0	5.588
	MMAE1	66.47	9.03	0	24.5	0	0	3.518
	MMAE2	88.74	10.26	0.5	0	0.50	0.2	3.549

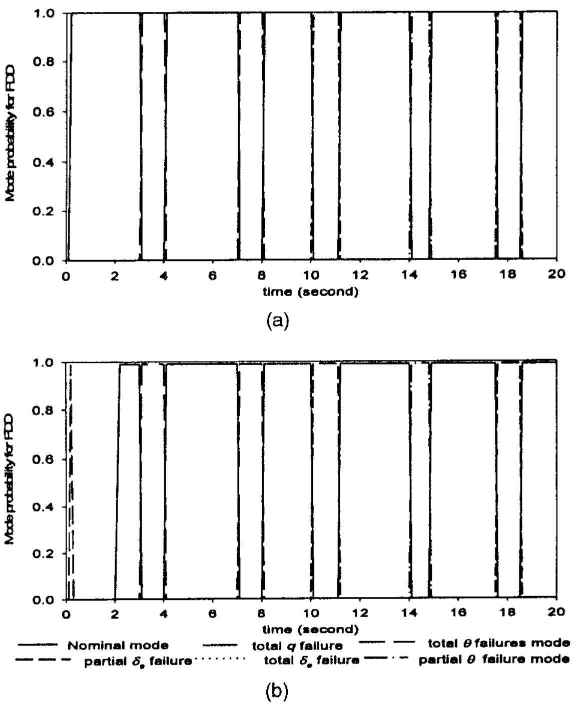

Fig. 4. Mode probabilities of single total and partial sensor and/or actuator failures. (a) IMM. (b) MMAE.

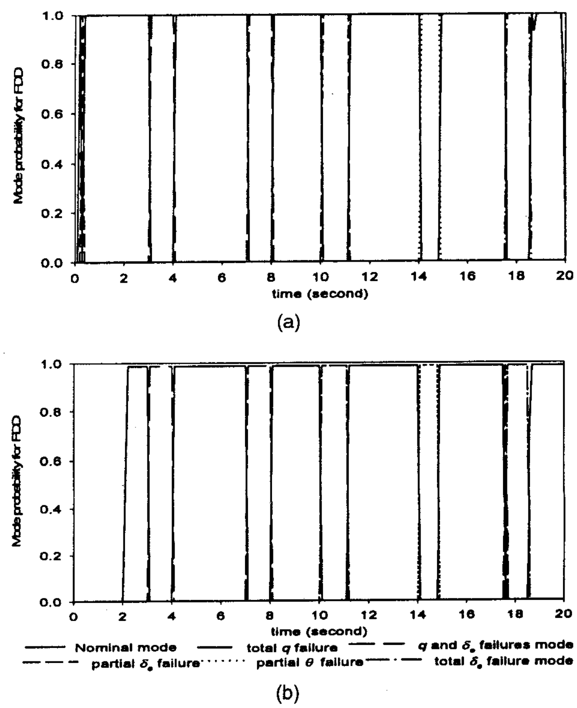

Fig. 5. Comparison of mode probabilities of simultaneous sensor and actuator failures. (a) IMM. (b) MMAE.

effectively. Two choices of the quantization of the partial fault magnitude $\mathcal{M}_s^1 = \{0, 0.5, 1\}$ and $\mathcal{M}_s^2 = \{0, 0.25, 0.5, 0.75, 1\}$ were considered. Other quantization levels may of course be used. We may design multiple models to correspond to these levels. The quantization error reduces as more models are used. However, the use of more models will increase the computational requirement. The FDD performance indices and the flops ($\times 10^4$) are given in Table V for these two model designs. Design 1 used quantization $\mathcal{M}_s^1$ while Design 2 used $\mathcal{M}_s^2$. For example, for the case of a sensor fault, Design 1 used 9 models (one normal, four 50% partial sensor failure, four total sensor failures) and Design 2 used 17 models (one normal, four 25% partial sensor failure, four 50% partial sensor failure, four 75% partial sensor failure, four total sensor failures). For an actuator fault, similarly as before, only primary control surface failure was considered. This leads to 3 models for Design 1 and 5 models for Design 2.

2) *Robustness Analysis*: To evaluate the robustness of the different MM-based FDD approaches to the design of model transition probabilities, modeling errors, and noise statistics, the following were simulated: 1) different modeling errors ranging from 0 to 40%, 2) different noise statistics errors ranging from 1/20 to 20 times of the true system noise matrix Q and measurement noise matrix R, and 3) different transition probability design errors ranging from 50% to 150% of the sojourn time used in the IMM algorithm. In the first two situations, only CDID versus errors in modeling and noise statistics for Scenario 3 are plotted in Figs. 6 and 7 due to space limitation, where IMM1 represents

TABLE V
FDD Result Comparison for Random Fault Scenarios

Fault	Design	Algorithm	CDID	FA	IFID	MFD	NMD	Distance	Flops
actuator	1	IMM	97.80	0	0.97	1.23	0	0.0337	0.7789
		MMAE1	76.90	0	2.65	20.45	0	0.0645	0.6925
		MMAE2	95.59	0	2.74	1.67	0	0.0647	0.6916
	2	IMM	97.10	0	2.12	0.78	0	0.0209	1.392
		MMAE1	78.62	0	17.76	3.62	0	0.1305	1.157
		MMAE2	91.38	0	7.15	1.465	0.005	0.0532	1.158
sensor	1	IMM	89.52	0	1.58	8.23	0.675	0.0341	2.845
		MMAE1	83.32	0	6.845	8.905	0.925	0.1323	2.095
		MMAE2	83.38	0	6.93	8.86	0.825	0.1323	2.103
	2	IMM	90.81	0	3.25	5.235	0.705	0.0594	6.652
		MMAE1	78.82	0	14.31	5.14	1.73	0.0901	3.996
		MMAE2	79.07	0	14.40	5.08	1.45	0.1323	4.039

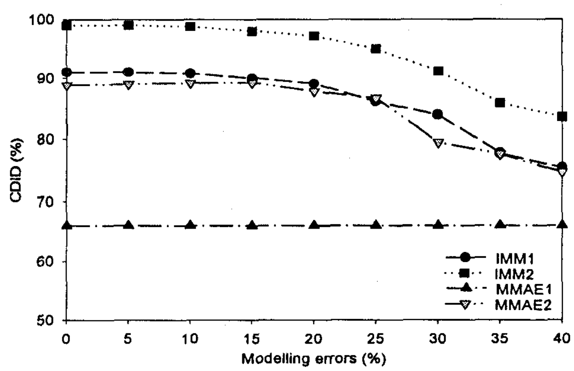

Fig. 6. Comparison of robustness to modeling errors.

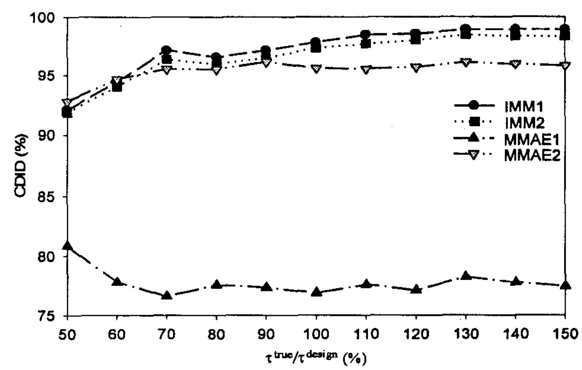

Fig. 8. CDID versus model transition probabilities errors.

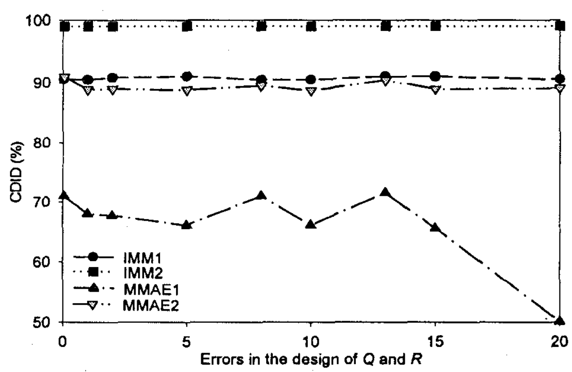

Fig. 7. Comparison of robustness to noise uncertainties.

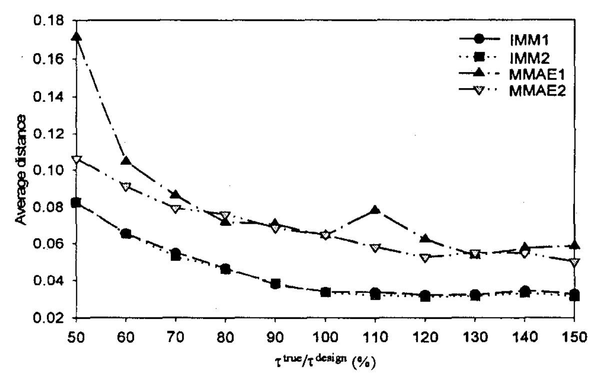

Fig. 9. Average modal distance versus model transition probability errors.

a numerically robust IMM algorithm implementation, IMM2 represents the IMM algorithm with a 10^{-300} lower bound on model transition probabilities. In the third situation, the CDID and average distance versus the errors in the designed model transition probabilities, based on the Design 1 of actuator fault in Scenario 4, are demonstrated in Figs. 8 and 9, respectively. These results show that the MM-based FDD approaches are robust to the design of model transition probabilities, modeling errors and the uncertainties in noise statistics. In addition, it is worth pointing out that the random test scenario has different sojourn time for different (normal or fault) modes at each run of the Monte Carlo simulation.

In Figs. 8 and 9, τ^{true} is the true mean sojourn time used to generate random scenarios as in (27); τ^{design} is the sojourn time used to obtain the mode transition probabilities, as given in (19), which is fixed as $\tau^{\text{design}}_{\text{normal}} = 3$, $\tau^{\text{design}}_{\text{fault}} = 1$, and $\tau^{\text{true}}/\tau^{\text{design}} = \tau^{\text{true}}_{\text{normal}}/\tau^{\text{design}}_{\text{normal}} = \tau^{\text{true}}_{\text{faultl}}/\tau^{\text{design}}_{\text{fault}}$. Note that MMAE algorithms do not use τ^{design} but τ^{true} varies in different cases, and thus they can still be treated as

TABLE VI
Comparison of FDD Results for Single Sensor and/or Actuator Failures

		CDID	FA	IFID	MFD	NMD	Delay	Flops
Case 1	IMM	99.00	1.00	0	0	0	0	56.00
	MMAE1	54.50	21.00	8.00	16.5	0	1.7	37.83
	MMAE2	77.31	18.03	3.5	0	1.17	1.3	37.91
Case 2	IMM	99.00	1.00	0	0	0	0	56.00
	MMAE1	55.00	20.5	8.00	16.5	0	1.6	37.83
	MMAE2	76.61	17.88	4.32	0	1.19	1.44	37.91
Case 3	IMM	99.00	1.00	0	0	0	0	55.96
	MMAE1	54.50	21.00	8.00	16.5	0	1.7	37.78
	MMAE2	76.62	18.00	3.5	0	1.88	1.3	37.87

if they had a $\tau^{\text{true}}/\tau^{\text{design}}$ ratio. Due to the randomness, average mode probabilities are meaningless. It is clear that the FDD performance of the IMM algorithm is overall much better than that of the MMAE approach, especially in terms of average modal distance. It should be noticed that for Design 1 of an actuator fault there are only 3 models in the model set. Even for this simple case, where there is enough separation between models, the IMM algorithm still obtains better FDD performance. For Design 2, the performance of the MMAE deteriorates. When more models are used, similar performance indices were obtained for Design 1 and Design 2.

From the results of the above scenarios, it can be seen that the IMM approach obviously outperforms the MMAE approach, especially with a lower bound on the model transition probabilities. The flops of the IMM is slightly greater than that of the MMAE approach. It is obvious that the numerical robust MMAE algorithm implementation, MMAE1, has much worse performance compared with the one (MMAE2) with a lower bound. On the other hand, better performance was obtained by the numerically robust IMM algorithm implementation (IMM1) without any artificial lower bound, although even better results can be obtained by the one (IMM2) with a lower bound.

Some other simulation results were obtained but not presented here. These results are for cases with different error strengths in which different model transition probabilities, modeling errors or errors in noise statistics were considered.

3) *FDD Results of Longitudinal and Lateral Dynamics*: For the FDD of longitudinal and lateral dynamics, only the total and partial sensor and/or actuator failures in a deterministic scenario were considered. For an actuator failure, only primary control surface, symmetric stabilator, aileron (δ_a), and rudder (δ_r), were considered to reduce the number of models used. There are 23 models in the model set: one normal, eight total sensor failure, eight 40% partial sensor failure, three total actuator failure, three 40% partial actuator failure models. Fig. 10 and Table VI show the FDD results when there is a total

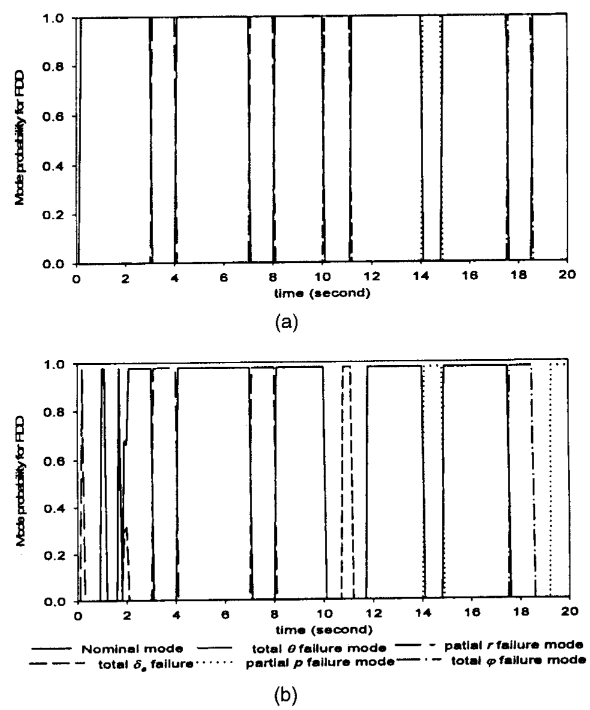

Fig. 10. Comparison of mode probabilities of single sensor and/or actuator failures. (a) IMM. (b) MMAE.

pitch angle failure between $k = 31$ and $k = 40$, a 40% partial yaw rate failure between $k = 71$ and 80, a total aileron failure between $k = 101$ and $k = 111$, a 40% partial roll failure between $k = 141$ and $k = 149$, and a total roll angle failure between $k = 176$ and $k = 185$. Much better FDD performance was obtained by the IMM approach than the MMAE approach.

D. FDD Results for Another Aircraft

The proposed IMM approach has also been applied to the FDD of another aircraft given in [29]. The FDD of longitudinal aircraft sensor and actuator failures with deterministic and random test scenarios were considered.

1) *Deterministic Scenario*: Similarly to scenario 3, the total and partial sensor and/or actuator failures, simultaneous partial sensor and actuator failures

TABLE VII
Performance Comparison of FDD for Simultaneous Sensor and Actuator Failures

		CDID	FA	IFID	MFD	NMD	Delay	Flops
Case 1	IMM	96.52	0.02	0.075	0.165	3.22	0.490	8.822
	MMAE1	61.62	13.35	0	24.5	0.53	0	4.767
	MMAE2	20.61	34.22	11.08	0.71	33.38	4.387	4.836
Case 2	IMM	96.59	0.015	0.115	0.08	3.19	0.469	8.822
	MMAE1	61.62	13.35	0	24.5	0.53	0	4.767
	MMAE2	20.62	34.34	11.22	0.64	33.18	4.492	4.836
Case 3	IMM	90.84	0.005	0.02	4.41	4.725	0.855	8.828
	MMAE1	61.60	13.29	0	24.5	0.61	0	4.767
	MMAE2	16.27	33.97	8.38	1.46	39.92	3.630	4.836

TABLE VIII
Performance Comparison for Random Fault Scenario

Fault	Design	Algorithm	CDID	FA	IFID	MFD	NMD	Distance	Flops
actuator	1	IMM	85.88	0	2.02	4.86	7.24	0.0372	1.353
		MMAE1	72.45	0	0.81	26.16	0.575	0.0923	1.109
		MMAE2	77.55	0	7.06	14.66	0.73	0.1275	1.110
	2	IMM	78.38	0	3.76	3.20	14.66	0.0291	2.799
		MMAE1	71.16	0	9.605	18.14	1.095	0.1089	2.008
		MMAE2	75.14	0	14.50	8.455	1.905	0.1048	2.016
sensor	1	IMM	74.21	0	11.74	0.56	13.50	0.0276	2.763
		MMAE1	62.62	0	14.03	1.49	21.86	0.0222	2.012
		MMAE2	75.92	0	15.52	1.59	6.97	0.0288	2.019
	2	IMM	71.10	0	11.49	0.38	17.03	0.0201	6.495
		MMAE1	44.92	0	14.41	0.81	39.86	0.0599	3.839
		MMAE2	67.11	0	17.43	1.03	14.42	0.0614	3.882

were simulated. There are 21 models in the model set: one normal, four total sensor failure, four 40% partial sensor failure, two total actuator failure, two 40% partial actuator failure, and eight simultaneous sensor and actuator failure models. Fig. 11 shows the mode probabilities when there is a total pitch rate failure between $k = 31$ and $k = 40$, a simultaneous 20% partial angle of attack and right elevator failures between $k = 71$ and 80, a 40% partial left elevator failure between $k = 101$ and $k = 111$, a 40% partial pitch angle failure between $k = 141$ and $k = 149$, and a total left elevator failure between $k = 176$ and $k = 185$. The FDD performance indices and the flops are given in Table VII. It is clear that the MMAE approach have much worse results than the IMM approach. Poor and sometimes misleading results were obtained by the MMAE algorithm. Note that the numerically robust MMAE1 has better performance than MMAE2 (with low bound) for this example.

2) *Random Scenario*: For this example, a similar modeling scheme as the first aircraft example was considered. For an actuator fault, there are 5 models in Design 1 and 9 models in Design 2. For a sensor fault, the same number of models as the first aircraft example was used. The results of Table VIII also support the superiority of the IMM approach to the MMAE approach. It is worth pointing out that the purpose for the simulation of random test scenarios

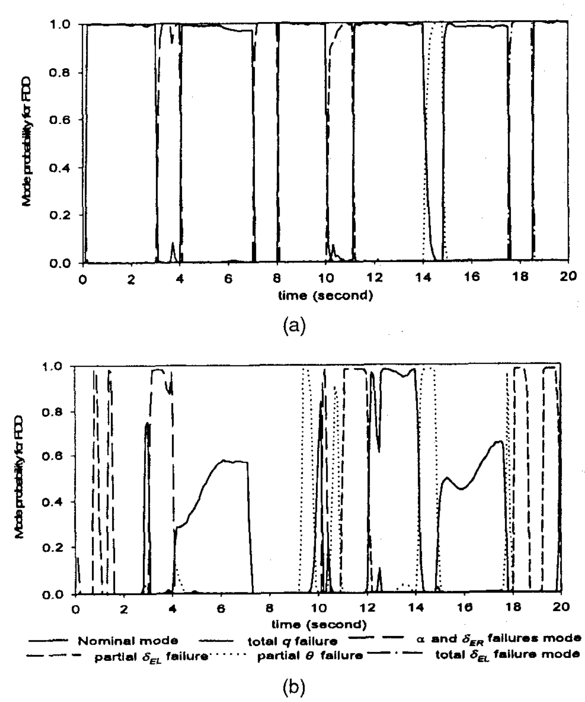

Fig. 11. Comparison of mode probabilities of simultaneous sensor and actuator failures. (a) IMM. (b) MMAE.

presented here is to compare the FDD performance of different algorithms.

E. Discussions

In the MMAE approach, to enhance the performance of detection and identification of flight control system actuator and/or sensor faults, various heuristic techniques were investigated, such as the removal of β dominance effect, bounded conditional probabilities, Kalman filter retuning, scalar penalty increase, probability smoothing, and increased residual propagation [24, 27]. These techniques do enhance the performance of the FDD but only in an *ad hoc* fashion; there is no solid foundation to believe that they are generally applicable. Some other similar heuristic modifications can be found in [10, 22]. It is clear that the IMM approach can obtain much better FDD performance without such heuristic adjustments, even though better FDD performance may be obtained by imposing an appropriate lower bound on model transition or mode probabilities.

It can be concluded from the simulations that the IMM approach outperforms significantly the MMAE algorithms. The former has a higher CDID, lower FA, IFID, MFD, NMD, and smaller detection delay. The IMM approach is also robust to the design of transition probabilities, the model modeling errors, and the errors in noise statistics. The more complex the fault scenario, the better improvement in its performance. The GPB1 algorithm was also evaluated via simulation of a number of test scenarios. Comparable performance with the IMM algorithm may be obtained for some, but not all scenarios. It depends on the complexity of the model set and test scenario used.

The main disadvantage of the IMM approach is its slightly higher computational complexity. However, its substantial improvement in the FDD performance pays for this price. With the rapid development of parallel computing techniques, it is even more attractive due to its inherent parallel structure.

To compare the MM-based FDD approach with single-model-based approach under the consideration of the ratio of performance and computational requirement, brief discussions are given as follows.

For the FDD of stochastic systems, Kalman filter is an essential tool for residual generation. Several statistical approaches can be used to evaluate residuals, such as chi-square test, SPRT, and GLR. Among these, the GLR [36] is the most popular and powerful for FDD. Thus we focus on the comparison of the GLR and the proposed IMM-based approach. In the GLR, a single Kalman filter designed under normal operation is used for residual generation. However, to perform fault detection, isolation and identification, a set of likelihoods has to be carried out for different faults. The basic idea of the GLR approach is that different abrupt changes have different effects on the filter residuals, i.e., different failure signatures, and the GLR calculates the likelihood of each possible event by correlating the residuals with the corresponding signatures. Besides, similarly to other hypothesis tests, a decision threshold for the GLR test has to be designed carefully and its value may vary with fault scenarios and systems. Another problem with single-model FDD approaches is that once a fault occurs, the previous normal state changes. This means that the designed Kalman filter based on normal operation of the system does not work correctly any more. As a result, such single-model approach can only deal with single faults. This can be seen from the examples in [10, 35]. To avoid such problem, an estimate update procedure was introduced [36]. For conventional (noninteracting) MM approach, to improve the FDD performance, a reinitialization procedure has to be carried out after a fault occurs due to probability "lock up," see, e.g. [35]. However, the IMM-based approach does not need such heuristic adjustment. For an MM approach with only a few models, its computational complexity differs from that of the GLR technique only slightly due to the additional need in computing likelihood in the latter. Only when many models are used in the MM approach, the difference may become significant. Please note that in this case the likelihood computation also grows greatly with the number of hypothesized fault modes. Meaningful results for ECG/VCG rhythm diagnosis and detection of highway incidents were presented in [10, 35], where performance of an MM approach and a GLR technique was compared but not for computational requirements. Satisfactory or better results were obtained by the MM approach [35]. Significant improvement with the IMM approach can be expected due to its superiority to the noninteracting MM approaches. It should be noted also that single faults were considered there. More general fault situations, including total/partial, single or double failures, and multiple faults have been simulated in this work.

Compared with the observer-based approach or other residual-based filters [33], another important characteristic or superiority of the IMM-based FDD approach is that it provides more reliable FDD information and accurate estimate not only when the system has failures, but also under normal conditions. In addition, it is easy to determine that the fault detection threshold and the FDD performance is not sensitive to it. When μ_T was set to a value other than 0.9, e.g. 0.5, similar FDD performance was obtained. Furthermore, random test scenarios were presented and used for the evaluation of the proposed FDD approach.

The simulation of the FDD of sensor and actuator failures of an F/A-18 aircraft and another aircraft demonstrated that the IMM approach is a powerful and easily implementable technique for the FDD of multiple failures. Although each single model is linear in this work, an extension to nonlinear models is straightforward as long as the Kalman filters are replaced by some nonlinear filters, e.g. extended Kalman filters or neural network estimators [12, 37, 39].

VI. CONCLUSIONS

In this paper, based on the IMM estimation algorithm, a new FDD approach for multiple failures of a dynamic system has been proposed. The proposed approach provides an integral framework for fault detection, diagnosis, and state estimation. Magill's MMAE algorithm and a numerically robust implementation developed in [19] have also been implemented and their performance was compared with that of the proposed one. The simulation results of sensors and actuators of two types of high performance aircraft for different deterministic and random test scenarios demonstrated that the proposed IMM approach have significantly better performance than the MMAE-based approach in terms of correctness, robustness and timeliness. Also, the inherent parallel structure of the IMM algorithm makes it attractive for real-time FDD. Future work includes the FDD of nonlinear dynamic systems and reconfigurable control.

APPENDIX A

The coefficients of the matrices A and B for the continuous-time state space model of F/A-18 aircraft were adopted from [31]:

$$A = \begin{bmatrix} -0.0133 & 0.07127 & 0.0 & -32.17 & 0.0 & 0.0 & 0.0 & 0.0 \\ -0.0728 & -1.14 & 641.92 & -1.460 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & -0.0127 & -0.947 & 0.0005 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 1.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & -0.245 & -646.9 & 0.0285 & 32.189 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.00849 & -0.246 & 0.112 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & -0.0256 & 0.73 & -2.83 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 1.0 & 0.0 \end{bmatrix}$$

$$B = \begin{bmatrix} 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ -129.5 & 19.43 & -149.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ -15.6 & -1.609 & 1.499 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & -6.93 & 0.0 & -2.915 & 34.909 \\ 0.0 & 0.0 & 0.0 & 0.0 & -0.396 & -0.835 & -0.896 & -3.26 \\ 0.0 & 0.0 & 0.0 & 0.0 & 11.86 & 13.06 & 13.14 & 4.4 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \end{bmatrix}$$

APPENDIX B

The coefficients of the matrices A and B for the continuous-time state space model were adopted from [29]:

$$A = \begin{bmatrix} -0.5091 & 1.0 & -0.0001 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ -7.6691 & -0.7111 & -0.0026 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 27.1241 & 0.0 & -0.0038 & -31.175 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 1.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & -0.0952 & 0.0 & -1.0 & 0.0367 \\ 0.0 & 0.0 & 0.0 & 0.0 & -19.004 & -1.2144 & 0.3849 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 5.5422 & -0.0065 & -0.2532 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 1.0 & 0.0 \end{bmatrix}$$

$$B = \begin{bmatrix} -0.028 & -0.028 & -0.028 & -0.028 & -0.021 & -0.021 & 0.0 & 0.0 \\ -5.639 & -5.639 & 6.8199 & 6.8199 & -2.9152 & -2.9152 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & -0.0022 & 0.007 \\ 12.038 & -12.038 & 13.132 & -13.132 & 24.623 & -24.623 & 1.3839 & 1.7057 \\ -0.2593 & 0.2593 & -0.2829 & 0.2829 & -0.5305 & 0.5305 & -0.2491 & -2.7469 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \end{bmatrix}.$$

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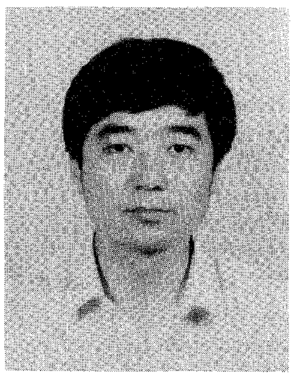

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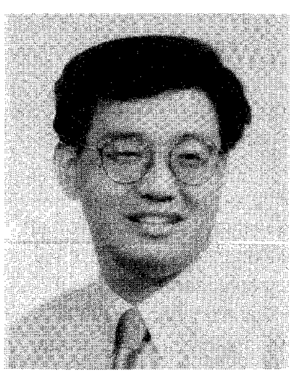

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