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Protocol-Based Fault Detection for Discrete Delayed Systems With Missing Measurements: The Uncertain Missing Probability Case

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ABSTRACT This paper is concerned with the protocol-based fault detection problem for a class of discrete systems with mixed time delays and missing measurements under uncertain missing probabilities. The phenomenon of missing measurements is characterized by a set of Bernoulli random variables, where each sensor could have individual missing probability and the corresponding occurrence probability could be uncertain. In order to mitigate the communication load of the network and reduce the incidence of the data collisions in the engineering reality, the round-robin (RR) protocol is employed to regulate the data transmission orders. The purpose of the addressed problem is to design a fault detection filter such that, in the simultaneous presence of mixed time delays, missing measurements, and RR protocol mechanism, the resulted filtering error system is asymptotically mean-square stable with a satisfactory H_∞ performance. In particular, some sufficient conditions are derived in terms of certain matrix inequalities and the explicit expression of the required filter parameters is proposed. Finally, a numerical example is employed to illustrate the effectiveness of the designed fault detection scheme.

INDEX TERMS Discrete-time system, fault detection, mixed time-delays, missing measurements, round-robin protocol, uncertain missing probabilities.

I. INTRODUCTION

The fault refers to the system performance beyond the expected changes, which might lead to the system deviations from normal operation. When the fault occurs, all or partial of system parameters may exhibit different characteristics from the normal states, and these differences contain a wealth of fault information [1]–[4]. Accordingly, it should be noted that there will lead to danger or disaster if the fault cannot be promptly detected and repaired, such as economic losses, environmental damage and even casualties [5]–[7]. As such, the fault must be diagnosed as early as possible to avoid serious consequences. Recently, the fault detection and fault estimation techniques are shown to be the effective approaches to enhance the system reliability, which have attracted considerable attention in many fields, see [8]–[10] and the references therein. Generally, the main tasks of fault detection include two parts: residual generation and residual evaluation [11]–[13]. On one hand, the residual generation refers to generate a residual signal based on the system's mathematical model and observable variables, which can reflect the fault information. When no fault occurs, the value of the residual signal is zero or near zero. When the fault occurs, the residual signal should be changed greatly so that the fault diagnosis system can detect the fault more sensitively. On the other hand, the residual evaluation corresponds to the analysis of the residual signal based on certain criterion, where the threshold value and fault diagnostic logic can be given according to the residual evaluation function. Moreover, the fault estimation process can be made to obtain the exhaustive information of the faults, such as quantity, size and type, and provides relevant information for subsequent fault tolerant control.

It is well recognized that the model-based fault detection problems have been widely discussed in recent years since the model-based fault detection filter method performs well on the purpose of detecting fault signals. Until now, a great number of outstanding results on fault detection problem have been presented, see [14]–[17] and the references therein. As is known to all, because of the speed limit of signal transmission and network congestion, the time-delay is commonly inevitable in data transmission, which may reduce the system performance or even lead to the instability of the whole system [18]. Therefore, it is meaningful to investigate the fault detection problem for systems with time-delays [19]–[24]. To mention a few, a fault detection filter has been designed in [20] for a class of discrete-time systems with multiple discrete time-delays as well as infinite distributed delays, where new sufficient conditions have been derived such that the fault detection dynamics system is exponentially stable in the mean-square sense and the error between the residual signal and the fault signal has been made as small as possible. In [21], the effects from the time-varying delay and nonlinear perturbations onto the event-based fault detection filtering performance have been examined, and the explicit expression of the desired filter gains has been presented in terms of the feasible solution to certain matrix inequalities.

Due to the limited bandwidth of the communications network, the data collisions are usually unavoidable, which will lead to unexpected phenomena, such as communication delays, data disorders and so on [25]. Recently, some communication protocols have been adopted to reduce the communication load, such as the round-robin (RR) protocol, try-once-discard protocol [26]–[28]. The RR protocol is a periodic scheduling scheme, where each node accesses the communication network based on a cyclical order. Such a protocol has received a lot of research attention, see [29]–[31]. For instance, the H_∞ fault detection algorithm has been given in [29] for 2-D systems with random fractional uncertainties under the RR protocol mechanism. It should be noticed that the RR protocol has been widely utilized in practical engineering, such as the ATM user-oriented satellite system as well as the multiprocessor bus arbitration, which makes it more realistic for us to discuss the influence of the RR protocol on the fault detection problems for complex dynamics systems. On the other hand, the missing measurements sometimes occur due to the unreliability of the network environments. Accordingly, many research results have been published about the fault detection problem for systems with missing measurements [32]–[34]. Specifically, the problem of fault detection has been addressed in [33] for networked control systems with signal quantization and packet dropouts, where the corresponding fault detection problem has already been converted into an H_∞ filtering problem, and a sufficient condition has been obtained to guarantee stochastic stability of the fault detection system with a prescribed H_∞ performance level. Nevertheless, few results can be applied to deal with the fault detection problem subject to missing measurements particularly the uncertain missing probabilities [35]. Compared with the rich literatures on the issues of state estimation and control under the RR protocol, to the best of the authors' knowledge, the fault detection problem for discrete systems with mixed delays and missing measurements under the RR protocol has not been fully discussed yet, which constitutes the major motivation of the current paper.

Motivated by the above discussions, in this paper, we aim to handle the fault detection problem for discrete systems with mixed time-delays and missing measurements under the RR protocol. Because of the limited communication resources, we utilize the RR protocol to regulate the order of data transmission and then reduce the bandwidth usage, i.e., it is assumed that only one sensor node can transmit the measurement signal at each moment. A set of mutually independent Bernoulli random variables is introduced to describe the phenomenon of the missing measurements and the uncertain occurrence probabilities are characterized by known constants. Sufficient conditions are presented to guarantee that the fault detection system is asymptotically stable in the mean-square sense and satisfies H_∞ performance. Furthermore, the expression form of the desired filter gains is derived. The main challenges can be listed as follows: (1) How to establish appropriate Lyapunov functional that can reflect the scheduling characteristics of the RR protocol? (2) How to select suitable method to deal with the impact of mixed delays and uncertain missing probabilities on system performance and propose an effective fault detection scheme? Accordingly, the main contributions of this paper lie in the following three aspects: (1) the fault detection problem is, for the first time, discussed for the discrete system subject to mixed time-delays and missing measurements; (2) in order to mitigate the communication load of the network with limit resource, the RR protocol is adopted when handling the fault detection problem; and (3) the uncertain missing probabilities are considered to better reflect the engineering reality and new fault detection scheme with expression form of the fault detection filter gain is developed.

The remainder of this article is organized as follows. In Section II, the discrete system model is established that takes the mixed time-delays, missing measurements and RR protocol into account, and the H_∞ filtering problem is formulated. In Section III, sufficient conditions are obtained to ensure that the error dynamics system is asymptotically stable in the mean-square sense and satisfies H_∞ performance. Furthermore, in the same section, the specific expression of the desired filter gains is given. In Section IV, a numerical example is provided to illustrate the effectiveness of the designed fault detection filtering scheme. This article is concluded in Section V.

Notations: The following notations are used in this paper. $\mathbb{R}^n$, $\mathbb{R}^{n\times m}$ and $\mathbb{Z}$ ($\mathbb{Z}^+$, $\mathbb{Z}^-$) denote, respectively, the n-dimensional Euclidean space, the set of all $n \times m$ real matrices and the set of integers (nonnegative integers, negative integers); $l_2[0, \infty)$ represents the space of square-summable vectors over $[0, \infty)$; $\| x \|$ refers to the standard l_2 norm of x, that is, $\| x \| = (x^T x)^{1/2}$; the notation $X \geq Y$ (respectively, $X > Y$), where X and Y are real symmetric matrices, means that $X - Y$ is positive semi-definite (respectively, positive definite); the superscript T and (-1) stand for the matrix transposition and matrix inverse, respectively; I and 0 represent the identity matrix and zero matrix with compatible dimensions; diag$\{\cdots\}$ means a block-diagonal matrix; $\mathbb{E}\{x\}$ refers to the expectation for a random variable x; Prob$\{\cdot\}$ is the occurrence probability of the event "$\cdot$". In symmetric block matrices, "$*$" is used as an ellipsis for terms induced by symmetry. Matrices, if they are not explicitly specified, are assumed to have compatible dimensions.

II. PROBLEM FORMULATION AND PRELIMINARIES

In this paper, the schematic diagram of the protocol-based fault detection filtering problem for discrete system with missing measurements is depicted in Fig. 1. For the purpose of avoiding data conflicts and reducing the communication load of the communication network, the RR protocol is adopted. Moreover, a fault detection mechanism is presented to generate the residual signal in order to detect the faults.

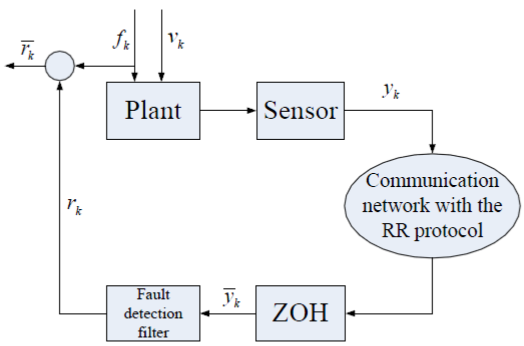

FIGURE 1. The fault detection filtering problem under RR protocol.

Consider the following discrete delayed system subject to missing measurements under uncertain missing probabilities:

$$\begin{cases} x_{k+1} = Ax_k + A_{d1}x_{k-\tau_k} + A_{d2}\sum_{d=1}^{\infty} \mu_d x_{k-d} \\ \qquad + D_1 v_k + G f_k, \\ y_k = \Lambda C x_k + D_2 v_k, \\ x_k = \varphi_k, \quad \forall k \in \mathbb{Z}^- \end{cases} \tag{1}$$

where $x_k \in \mathbb{R}^n$ stands for the state vector, $y_k \in \mathbb{R}^m$ represents the measured output vector, $v_k \in \mathbb{R}^s$ denotes the external disturbance belonging to $l_2([0, \infty); \mathbb{R}^s)$, and $f_k \in \mathbb{R}^l$ is the fault to be detected. τ_k is a time-varying delay which satisfies $\tau_m \leq \tau_k \leq \tau_M$ with τ_m and τ_M being the known bounds. d $(d = 1, 2, \cdots, \infty)$ describes the distributed time delay. φ_k is a given initial sequence. A, A_{d1}, A_{d2}, D_1, G, C and D_2 are known constant matrices with appropriate dimensions. The scalars $\mu_d \geq 0$ $(d = 1, 2, \cdots, \infty)$ satisfy the following convergence condition:

$$\bar{\mu} \triangleq \sum_{d=1}^{\infty} \mu_d \leq \sum_{d=1}^{\infty} d\mu_d < +\infty. \tag{2}$$

The phenomenon of missing measurements is modeled by the matrix $\Lambda = \text{diag}\{\lambda_1, \lambda_2, \cdots, \lambda_m\} = \sum_{i=1}^{m} \lambda_i E_i$, where $E_i = \text{diag}\{\underbrace{0, \cdots, 0}_{i-1}, 1, \underbrace{0, \cdots, 0}_{m-i}\}$ and λ_i are mutually independent Bernoulli random variables having statistical characteristics:

$$\begin{aligned} &\text{Prob}\{\lambda_i = 1\} = \mathbb{E}\{\lambda_i\} = \bar{\lambda}_i + \Delta\bar{\lambda}_i, \\ &\text{Prob}\{\lambda_i = 0\} = 1 - \mathbb{E}\{\lambda_i\} = 1 - (\bar{\lambda}_i + \Delta\bar{\lambda}_i), \end{aligned} \tag{3}$$

where $\mathbb{E}\{\lambda_i\}$ $(i = 1, 2, \cdots, m)$ denotes the mathematical expectation of λ_i and $\bar{\lambda}_i$ are known scalars. Moreover, $|\Delta\bar{\lambda}_i| \leq \epsilon_i$ with ϵ_i being known scalars.

Remark 1: In some practical situations, it is not easy to obtain the accurate value of the expectation of λ_i probably due to the inaccuracy statistical tests or other reasons. Hence, $\Delta\bar{\lambda}_i$ is employed to describe the uncertain missing probability. Thus, the fault detection problem with missing measurements under uncertain missing probabilities is addressed in this paper. Specifically, a diagonal matrix consisting of a series of mutually independent Bernoulli random variables is employed to characterize the case that each sensor could have individual missing probability, and the uncertain missing probabilities are depicted by (3) with known bounds ϵ_i of the probabilities. Such an expression can better depict the situation when the systems operate within changeable communication environment, which often occur in the networked setting. Moreover, it should be pointed out that the description of the traditional missing measurements can be easily derived by setting $\Delta\bar{\lambda}_i = 0$.

In order to avoid the data conflicts, it is generally assumed that only one node is physically allowed to transmit the measurement data over the communication network at each transmission instant. In this case, the RR protocol can be employed to determine which node gets access to the communication network at certain transmission step. In particular, the RR protocol assigns the utilization rights of the communication network to the network nodes in the chronological order. That is to say, each node could gain the transmission opportunities in a cyclical order under this protocol scheduled.

Let $h_k \in \{1, 2, \cdots, m\}$ be the node that obtains the network authority at the k-th instant, and set $h_k = k$ when $k \in \{1, 2, \cdots, m\}$. Under the RR protocol, the value of h_k obeys the rule $h_{k+m} = h_k$ for all $k \in \mathbb{N}^+$. Therefore, h_k can be defined as follows:

$$h_k = \text{mod}(k-1, m) + 1.$$

Denote $\bar{y}_k = [\bar{y}_{1,k}^T \;\; \bar{y}_{2,k}^T \;\; \cdots \;\; \bar{y}_{m,k}^T]^T$ as the output after transmission over the communication network under the RR protocol. The updating rule of $\bar{y}_{i,k}$ $(i = 1, 2, \cdots, m)$ can be given as follows:

$$\bar{y}_{i,k} = \begin{cases} y_{i,k}, & \text{if } i = h_k, \\ \bar{y}_{i,k-1}, & \text{otherwise.} \end{cases} \tag{4}$$

Based on above updating rule (4), the actual received measurement can be described by the following form:

$$\begin{aligned} \bar{y}_k &= \Phi_{h_k} y_k + (I - \Phi_{h_k})\bar{y}_{k-1} \\ &= \Phi_{h_k}\tilde{\Lambda}Cx_k + \Phi_{h_k}(\Lambda - \tilde{\Lambda})Cx_k + \Phi_{h_k}D_2 v_k \\ &\quad + (I - \Phi_{h_k})\bar{y}_{k-1}, \end{aligned} \tag{5}$$

where $\Phi_{h_k} = \text{diag}\{\delta_{h_k,1}, \delta_{h_k,2}, \cdots, \delta_{h_k,m}\}$ denotes the update matrix and $\delta_{h_k,i} \in \{0, 1\}$ is the Kronecker delta function. Moreover, $\tilde{\Lambda} = \text{diag}\{\bar{\lambda}_1 + \Delta\bar{\lambda}_1, \cdots, \bar{\lambda}_m + \Delta\bar{\lambda}_m\}$ is the mathematical expectation of Λ. Then, it is easy to see that $\mathbb{E}\{\Lambda - \tilde{\Lambda}\} = 0$.

Denote

$$\begin{aligned} \tilde{\Lambda} &= \text{diag}\{\bar{\lambda}_1, \cdots, \bar{\lambda}_m\} + \text{diag}\{\Delta\bar{\lambda}_1, \cdots, \Delta\bar{\lambda}_m\} \\ &= \bar{\Lambda} + \Delta\bar{\Lambda}. \end{aligned}$$

According to $|\ \Delta\bar{\lambda}_i\ | \leq \epsilon_i$ and letting

$$\begin{aligned} \Lambda_1 &= \text{diag}\{\epsilon_1, \cdots, \epsilon_m\}, \\ \Lambda_2 &= \text{diag}\{\varsigma_1, \cdots, \varsigma_m\},\ |\ \varsigma_i\ | \leq \epsilon_i, \end{aligned}$$

then, $\Delta\bar{\Lambda}$ can be described as $\Delta\bar{\Lambda} = \Lambda_2$, where $\Lambda_2 \in [-\Lambda_1,\ \Lambda_1]$. It is worth noting that $\Lambda_2 \in [-\Lambda_1,\ \Lambda_1]$ means $\varsigma_i \in [-\epsilon_i,\ \epsilon_i]$. Defining $\Gamma = \Lambda_2\Lambda_1^{-1}$, the matrix $\Delta\bar{\Lambda}$ can be further written as follows:

$$\Delta\bar{\Lambda} = \Gamma\Lambda_1, \quad \Gamma^T\Gamma = \Gamma\Gamma^T \leq I.$$

Therefore,

$$\tilde{\Lambda} = \bar{\Lambda} + \Gamma\Lambda_1. \tag{6}$$

Remark 2: Under the RR protocol, only the measurement of the node has the access right that can be transmitted to the filter at each instant. For the measurements collected by m sensors, the i-th ($i = 1, 2, \cdots, m$) mode is used to reflect that the i-th sensor has the transmission permission, i.e., $\bar{y}_{i,k} = y_{i,k}$. Meanwhile, by utilizing a zero-order holder (ZOH), the measurement which does not acquire the authority to access the communication network will be compensated by the received measurement signals stored at the receiver side, namely $\bar{y}_{i,k} = \bar{y}_{i,k-1}$, which can effectively reduce the total amount of data transmission. It is not difficult to see from (5) that $\bar{y}_k$ contains the term $(I - \Phi_{h_k})\bar{y}_{k-1}$, which will bring difficulties to the later analysis. In addition, it's worth noting that the RR protocol provides a deterministic periodic scheduling scheme. However, the stochastic communication protocol (SCP) performs a random way to determining the node which can send the measurement signal over the network at each communication time step, and some interesting fault detection methods can be expected.

Define $\bar{x}_k = [x_k^T\ \ \bar{y}_{k-1}^T]^T \in \mathbb{R}^{n+m}$. Combining (1) with (5) yields the following augmented system:

$$\begin{cases} \bar{x}_{k+1} = (\bar{A}_{h_k,1} + \bar{A}_{h_k,2} + \bar{A}_{h_k,3})\bar{x}_k + \bar{A}_{d1}\bar{x}_{k-\tau_k} \\ \qquad\quad + \bar{A}_{d2}\sum_{d=1}^{\infty}\mu_d\bar{x}_{k-d} + \bar{D}_{h_k}v_k + \bar{G}f_k, \\ \bar{y}_k = (\bar{C}_{h_k,1} + \bar{C}_{h_k,2} + \bar{C}_{h_k,3})\bar{x}_k + \Phi_{h_k}D_2v_k, \end{cases} \tag{7}$$

where

$$\begin{aligned} &\bar{A}_{h_k,1} = \begin{bmatrix} 0 & 0 \\ \Phi_{h_k}(\Lambda - \tilde{\Lambda})C & 0 \end{bmatrix}, \quad \bar{A}_{h_k,2} = \begin{bmatrix} A & 0 \\ 0 & I - \Phi_{h_k} \end{bmatrix}, \\ &\bar{A}_{h_k,3} = \begin{bmatrix} 0 & 0 \\ \Phi_{h_k}\tilde{\Lambda}C & 0 \end{bmatrix}, \quad \bar{A}_{d1} = \begin{bmatrix} A_{d1} & 0 \\ 0 & 0 \end{bmatrix}, \\ &\bar{A}_{d2} = \begin{bmatrix} A_{d2} & 0 \\ 0 & 0 \end{bmatrix}, \quad \bar{D}_{h_k} = \begin{bmatrix} D_1 \\ \Phi_{h_k}D_2 \end{bmatrix}, \quad \bar{G} = \begin{bmatrix} G \\ 0 \end{bmatrix}, \\ &\bar{C}_{h_k,1} = \begin{bmatrix} \Phi_{h_k}(\Lambda - \tilde{\Lambda})C & 0 \end{bmatrix}, \quad \bar{C}_{h_k,2} = \begin{bmatrix} 0 & I - \Phi_{h_k} \end{bmatrix}, \\ &\bar{C}_{h_k,3} = \begin{bmatrix} \Phi_{h_k}\tilde{\Lambda}C & 0 \end{bmatrix}. \end{aligned}$$

According to the previous analysis, we can obtain that

$$\mathbb{E}\{\bar{A}_{h_k,1}\} = 0 \quad \text{and } \mathbb{E}\{\bar{C}_{h_k,1}\} = 0.$$

Remark 3: According to (5), we can see that the measurement $\bar{y}_k$ contains $\bar{y}_{k-1}$. Therefore, the augmentation method is used here to help subsequent analysis, i.e., $\bar{x}_k = [x_k^T\ \ \bar{y}_{k-1}^T]^T$, then the dynamics system (7) can be obtained.

In order to detect the fault of the augmented system (7) subject to the RR protocol, we construct the following discrete fault detection filter:

$$\begin{cases} \hat{\bar{x}}_{k+1} = \bar{A}_{h_k,F}\hat{\bar{x}}_k + \bar{B}_{h_k,F}\bar{y}_k, \\ r_k = \bar{D}_{h_k,F}\hat{\bar{x}}_k + \bar{E}_{h_k,F}\bar{y}_k, \end{cases} \tag{8}$$

where $\hat{\bar{x}}_k \in \mathbb{R}^{n+m}$ is the state of the fault detection filter, $r_k \in \mathbb{R}^l$ is the so-called residual that is compatible with f_k, $\bar{A}_{h_k,F}$, $\bar{B}_{h_k,F}$, $\bar{D}_{h_k,F}$ and $\bar{E}_{h_k,F}$ are appropriately dimensioned filter matrices to be determined.

Let $\eta_k = [\bar{x}_k^T\ \hat{\bar{x}}_k^T]^T$, $\bar{r}_k = r_k - f_k$ and $\vartheta_k = [v_k^T\ \ f_k^T]^T$. From (7) and (8), we have the following error dynamics system:

$$\begin{cases} \eta_{k+1} = (\tilde{A}_{h_k,1} + \tilde{A}_{h_k,2} + \tilde{A}_{h_k,3})\eta_k + \tilde{A}_{d1}\eta_{k-\tau_k} \\ \qquad\quad + \tilde{A}_{d2}\sum_{d=1}^{\infty}\mu_d\eta_{k-d} + \tilde{D}_{h_k,1}\vartheta_k, \\ \bar{r}_k = (\tilde{C}_{h_k,1} + \tilde{C}_{h_k,2} + \tilde{C}_{h_k,3})\eta_k + \tilde{D}_{h_k,2}\vartheta_k, \end{cases} \tag{9}$$

where

$$\begin{aligned} &\tilde{A}_{h_k,1} = \begin{bmatrix} \bar{A}_{h_k,1} & 0 \\ \bar{B}_{h_k,F}\bar{C}_{h_k,1} & 0 \end{bmatrix}, \quad \tilde{A}_{h_k,3} = \begin{bmatrix} \bar{A}_{h_k,3} & 0 \\ \bar{B}_{h_k,F}\bar{C}_{h_k,3} & 0 \end{bmatrix}, \\ &\tilde{A}_{h_k,2} = \begin{bmatrix} \bar{A}_{h_k,2} & 0 \\ \bar{B}_{h_k,F}\bar{C}_{h_k,2} & \bar{A}_{h_k,F} \end{bmatrix}, \quad \tilde{A}_{d1} = \begin{bmatrix} \bar{A}_{d1} & 0 \\ 0 & 0 \end{bmatrix}, \\ &\tilde{A}_{d2} = \begin{bmatrix} \bar{A}_{d2} & 0 \\ 0 & 0 \end{bmatrix}, \quad \tilde{D}_{h_k,1} = \begin{bmatrix} \bar{D}_{h_k} & \bar{G} \\ \bar{B}_{h_k,F}\Phi_{h_k}D_2 & 0 \end{bmatrix}, \\ &\tilde{D}_{h_k,2} = \begin{bmatrix} \bar{E}_{h_k,F}\Phi_{h_k}D_2 & -I \end{bmatrix}, \\ &\tilde{C}_{h_k,1} = \begin{bmatrix} \bar{E}_{h_k,F}\bar{C}_{h_k,1} & 0 \end{bmatrix}, \\ &\tilde{C}_{h_k,2} = \begin{bmatrix} \bar{E}_{h_k,F}\bar{C}_{h_k,2} & \bar{D}_{h_k,F} \end{bmatrix}, \\ &\tilde{C}_{h_k,3} = \begin{bmatrix} \bar{E}_{h_k,F}\bar{C}_{h_k,3} & 0 \end{bmatrix}. \end{aligned}$$

Then, it is straightforward to see that $\mathbb{E}\{\tilde{A}_{h_k,1}\} = 0$ and $\mathbb{E}\{\tilde{C}_{h_k,1}\} = 0$.

From the above discussions, the original problem of fault detection filter for discrete systems with mixed time-delays and missing measurements under the RR protocol can be transformed into an H_∞ filtering problem, i.e., we aim to construct a filter of the form (8) such that the resulted filtering error dynamics system attains a prescribed H_∞ attenuation level. Namely, the purpose of this paper is to find the filter parameters $\bar{A}_{h_k,F}$, $\bar{B}_{h_k,F}$, $\bar{D}_{h_k,F}$ and $\bar{E}_{h_k,F}$ such that the following two requirements are satisfied simultaneously:

(R1) When $\vartheta_k = 0$, the error dynamics system (9) is asymptotically stable in the mean-square sense.

(R2) When $\vartheta_k \neq 0$, under zero-initial condition, the error $\bar{r}_k$ satisfies

$$\sum_{k=0}^{\infty} \mathbb{E}\left\{\| \bar{r}_k \|^2\right\} \leq \gamma^2 \sum_{k=0}^{\infty} \mathbb{E}\left\{\| \vartheta_k \|^2\right\}, \tag{10}$$

where γ is a positive scalar.

We further give a residual evaluation function J_k and a threshold J_{th} of the following form:

$$J_k = \left\{\sum_{h=0}^{k} r_h^T r_h\right\}^{1/2}, \quad J_{th} = \sup_{v_k \in l_2, f_k=0} \mathbb{E}\{J_k\}. \tag{11}$$

According to (11), the occurrence of faults can be detected by comparing J_k with J_{th} under the following rule:

$$J_k > J_{th} \Rightarrow \textit{a fault is detected} \Rightarrow \textit{alarm}$$
$$J_k \leq J_{th} \Rightarrow \textit{no fault} \Rightarrow \textit{no alarm}$$

III. MAIN RESULTS

In this section, our main goal is to derive the sufficient conditions to guarantee that the augmented system (9) with $\vartheta_k = 0$ is asymptotically stable in the mean-square sense and satisfies (10) under the zero-initial condition for all nonzero ϑ_k. Subsequently, the fault detection filter parameters are designed in terms of certain matrix inequalities.

Before giving our main results, let us introduce the following lemmas.

Lemma 1 [20]: Let $M \in \mathbb{R}^{n\times n}$ be a positive semi-definite matrix, $x_i \in \mathbb{R}^n$ $(i = 1, 2, \cdots)$, and constants $a_i > 0$ $(i = 1, 2, \cdots)$. If the series concerned is convergent, then the following inequality always holds:

$$\left(\sum_{i=1}^{\infty} a_i x_i\right)^T M \left(\sum_{i=1}^{\infty} a_i x_i\right) \leq \left(\sum_{i=1}^{\infty} a_i\right) \sum_{i=1}^{\infty} a_i x_i^T M x_i.$$

Lemma 2 [36] (Schur Complement): For a given matrix $S = \begin{bmatrix} S_{11} & S_{12} \\ S_{12}^T & S_{22} \end{bmatrix}$ with $S_{11}^T = S_{11}$ and $S_{22}^T = S_{22}$, then the following conditions are equivalent:

(1) $S < 0$;

(2) $S_{11} < 0, \quad S_{22} - S_{12}^T S_{11}^{-1} S_{12} < 0$;

(3) $S_{22} < 0, \quad S_{11} - S_{12} S_{22}^{-1} S_{12}^T < 0$.

Lemma 3 [20]: Let $N = N^T$, H and E be real matrices with appropriate dimensions, and let $F_k^T F_k \leq I$. Then, the inequality $N + HF_kE + (HF_kE)^T < 0$ if and only if there exists a positive scalar ε such that

$$N + \varepsilon^{-1} HH^T + \varepsilon E^T E < 0.$$

In what follows, a sufficient condition is given to ensure the asymptotically mean-square stability of the resulted error dynamics system (9) with prescribed H_∞ performance.

Theorem 1: Let the filter parameters $\bar{A}_{i,F}$, $\bar{B}_{i,F}$, $\bar{D}_{i,F}$ and $\bar{E}_{i,F}$ be given. For given positive scalars τ_m, τ_M and a prescribed H_∞ index $\gamma > 0$, the error dynamics system (9) with $\vartheta_k = 0$ is asymptotically stable in the mean-square sense and satisfies (10) under the zero-initial condition for all nonzero ϑ_k, if there exist symmetric positive definite matrices P_i $(i = 1, 2, \cdots, m)$, Q_1, Q_2, Q_3 and R satisfying

$$\hat{\Xi}^i = \begin{bmatrix} \Xi_{11}^i + L_1^i & * & * & * & * & * \\ 0 & -Q_1 & * & * & * & * \\ \Xi_{31}^i & 0 & \Xi_{33}^i & * & * & * \\ 0 & 0 & 0 & -Q_3 & * & * \\ \Xi_{51}^i & 0 & \Xi_{53}^i & 0 & \Xi_{55}^i & * \\ \Xi_{61}^i + L_2^i & 0 & \Xi_{63}^i & 0 & \Xi_{65}^i & \Xi_{66}^i + L_3^i \end{bmatrix} < 0, \tag{12}$$

where

$$\begin{aligned}
\Xi_{11}^i &= -P_i + Q_1 + (\tau_M - \tau_m + 1)Q_2 + Q_3 \\
&\quad + \bar{\mu}R + \sum_{j=1}^{m} \bar{\sigma}_j^2 (\tilde{A}_{i,1}^j)^T P_{i+1} (\tilde{A}_{i,1}^j) \\
&\quad + (\tilde{A}_{i,2} + \tilde{A}_{i,3})^T P_{i+1} (\tilde{A}_{i,2} + \tilde{A}_{i,3}), \\
\Xi_{31}^i &= \tilde{A}_{d1}^T P_{i+1} (\tilde{A}_{i,2} + \tilde{A}_{i,3}), \\
\Xi_{33}^i &= -Q_2 + \tilde{A}_{d1}^T P_{i+1} \tilde{A}_{d1}, \\
\Xi_{51}^i &= \tilde{A}_{d2}^T P_{i+1} (\tilde{A}_{i,2} + \tilde{A}_{i,3}), \quad \Xi_{53}^i = \tilde{A}_{d2}^T P_{i+1} \tilde{A}_{d1}, \\
\Xi_{55}^i &= -\frac{1}{\bar{\mu}} R + \tilde{A}_{d2}^T P_{i+1} \tilde{A}_{d2}, \quad \Xi_{66}^i = \tilde{D}_{i,1}^T P_{i+1} \tilde{D}_{i,1}, \\
\Xi_{61}^i &= \tilde{D}_{i,1}^T P_{i+1} (\tilde{A}_{i,2} + \tilde{A}_{i,3}), \quad \Xi_{63}^i = \tilde{D}_{i,1}^T P_{i+1} \tilde{A}_{d1}, \\
\Xi_{65}^i &= \tilde{D}_{i,1}^T P_{i+1} \tilde{A}_{d2}, \\
L_1^i &= \sum_{j=1}^{m} \bar{\sigma}_j^2 (\tilde{C}_{i,1}^j)^T (\tilde{C}_{i,1}^j) + (\tilde{C}_{i,2} + \tilde{C}_{i,3})^T (\tilde{C}_{i,2} + \tilde{C}_{i,3}), \\
L_2^i &= \tilde{D}_{i,2}^T (\tilde{C}_{i,2} + \tilde{C}_{i,3}), \; L_3^i = -\gamma^2 I + \tilde{D}_{i,2}^T \tilde{D}_{i,2}, \\
\tilde{A}_{i,1}^j &= \begin{bmatrix} \breve{A}_{i,1}^j & 0 \\ \bar{B}_{i,F} \breve{C}_{i,1}^j & 0 \end{bmatrix}, \; \breve{A}_{i,1}^j = \begin{bmatrix} 0 & 0 \\ \Phi_i E_j C & 0 \end{bmatrix}, \\
\tilde{C}_{i,1}^j &= \begin{bmatrix} \bar{E}_{i,F} \breve{C}_{i,1}^j & 0 \end{bmatrix}, \quad \breve{C}_{i,1}^j = \begin{bmatrix} \Phi_i E_j C & 0 \end{bmatrix}, \\
\bar{\sigma}_j^2 &= \min\{\frac{1}{4}, (\lambda_j + \epsilon_j)(1 - \lambda_j + \epsilon_j)\}
\end{aligned} \tag{13}$$

with $P_{m+i} = P_i$ for all $i \in \{1, 2, \cdots, m\}$.

Proof: In order to prove our result, we choose the following Lyapunov functional for system (9):

$$V_k = \sum_{i=1}^{3} V_{i,k}, \tag{14}$$

where

$$V_{1,k} = \eta_k^T P_{h_k} \eta_k,$$

$$V_{2,k} = \sum_{i=k-\tau_m}^{k-1} \eta_i^T Q_1 \eta_i + \sum_{i=k-\tau_k}^{k-1} \eta_i^T Q_2 \eta_i + \sum_{i=k-\tau_M}^{k-1} \eta_i^T Q_3 \eta_i + \sum_{j=-\tau_M+1}^{-\tau_m} \sum_{i=k+j}^{k-1} \eta_i^T Q_2 \eta_i,$$

$$V_{3,k} = \sum_{d=1}^{\infty} \mu_d \sum_{i=k-d}^{k-1} \eta_i^T R \eta_i.$$

For $h_k = i$, $h_{k+1} = i+1$, we compute the mathematical expectation of the difference of V_k along the trajectory of the augmented system (9) with $\vartheta_k = 0$. In terms of $\mathbb{E}\{\Delta V_{i,k}\} = \mathbb{E}\{V_{i,k+1}\} - \mathbb{E}\{V_{i,k}\}$, we have

$$\mathbb{E}\{\Delta V_k\} = \mathbb{E}\left\{\Delta V_{1,k} + \Delta V_{2,k} + \Delta V_{3,k}\right\},$$

where

$$\begin{aligned}
&\mathbb{E}\left\{\Delta V_{1,k}\right\} \\
&= \mathbb{E}\left\{\eta_{k+1}^T P_{i+1} \eta_{k+1} - \eta_k^T P_i \eta_k\right\} \\
&= \mathbb{E}\Bigg\{\Bigg[\eta_k^T (\tilde{A}_{i,1} + \tilde{A}_{i,2} + \tilde{A}_{i,3})^T + \eta_{k-\tau_k}^T \tilde{A}_{d1}^T \\
&\quad + \left(\sum_{d=1}^{\infty} \mu_d \eta_{k-d}\right)^T \tilde{A}_{d2}^T + \vartheta_k^T \tilde{D}_{i,1}^T\Bigg] P_{i+1} \\
&\quad \times \Bigg[(\tilde{A}_{i,1} + \tilde{A}_{i,2} + \tilde{A}_{i,3})\eta_k + \tilde{A}_{d1}\eta_{k-\tau_k} \\
&\quad + \tilde{A}_{d2} \sum_{d=1}^{\infty} \mu_d \eta_{k-d} + \tilde{D}_{i,1}\vartheta_k\Bigg] - \eta_k^T P_i \eta_k\Bigg\} \\
&= \sum_{j=1}^{m} \sigma_j^2 \eta_k^T (\tilde{A}_{i,1}^j)^T P_{i+1} (\tilde{A}_{i,1}^j) \eta_k \\
&\quad + \eta_k^T (\tilde{A}_{i,2} + \tilde{A}_{i,3})^T P_{i+1} (\tilde{A}_{i,2} + \tilde{A}_{i,3}) \eta_k \\
&\quad + \eta_{k-\tau_k}^T \tilde{A}_{d1}^T P_{i+1} \tilde{A}_{d1} \eta_{k-\tau_k} + \vartheta_k^T \tilde{D}_{i,1}^T P_{i+1} \tilde{D}_{i,1} \vartheta_k \\
&\quad + \left(\sum_{d=1}^{\infty} \mu_d \eta_{k-d}\right)^T \tilde{A}_{d2}^T P_{i+1} \tilde{A}_{d2} \left(\sum_{d=1}^{\infty} \mu_d \eta_{k-d}\right) \\
&\quad + 2\eta_k^T (\tilde{A}_{i,2} + \tilde{A}_{i,3})^T P_{i+1} \tilde{A}_{d1} \eta_{k-\tau_k} \\
&\quad + 2\eta_k^T (\tilde{A}_{i,2} + \tilde{A}_{i,3})^T P_{i+1} \tilde{A}_{d2} \left(\sum_{d=1}^{\infty} \mu_d \eta_{k-d}\right) \\
&\quad + 2\eta_k^T (\tilde{A}_{i,2} + \tilde{A}_{i,3})^T P_{i+1} \tilde{D}_{i,1} \vartheta_k \\
&\quad + 2\eta_{k-\tau_k}^T \tilde{A}_{d1}^T P_{i+1} \tilde{A}_{d2} \left(\sum_{d=1}^{\infty} \mu_d \eta_{k-d}\right) \\
&\quad + 2\eta_{k-\tau_k}^T \tilde{A}_{d1}^T P_{i+1} \tilde{D}_{i,1} \vartheta_k - \eta_k^T P_i \eta_k \\
&\quad + 2\left(\sum_{d=1}^{\infty} \mu_d \eta_{k-d}\right)^T \tilde{A}_{d2}^T P_{i+1} \tilde{D}_{i,1} \vartheta_k,
\end{aligned} \tag{15}$$

$$\begin{aligned}
&\mathbb{E}\left\{\Delta V_{2,k}\right\} \\
&\leq \eta_k^T [Q_1 + (\tau_M - \tau_m + 1) Q_2 + Q_3] \eta_k \\
&\quad - \eta_{k-\tau_m}^T Q_1 \eta_{k-\tau_m} - \eta_{k-\tau_k}^T Q_2 \eta_{k-\tau_k} \\
&\quad - \eta_{k-\tau_M}^T Q_3 \eta_{k-\tau_M},
\end{aligned} \tag{16}$$

$$\begin{aligned}
&\mathbb{E}\left\{\Delta V_{3,k}\right\} \\
&= \bar{\mu} \eta_k^T R \eta_k - \sum_{d=1}^{\infty} \mu_d \eta_{k-d}^T R \eta_{k-d}.
\end{aligned} \tag{17}$$

Here, $\sigma_j^2 = (\bar{\lambda}_j + \Delta\bar{\lambda}_j)(1 - \bar{\lambda}_j - \Delta\bar{\lambda}_j)$, $\tilde{A}_{i,1}^j$ is given in (13).

Noting that $\sigma_j^2 \leq \bar{\sigma}_j^2$, we obtain

$$\begin{aligned}
&\mathbb{E}\left\{\Delta V_{1,k}\right\} \\
&\leq \sum_{j=1}^{m} \bar{\sigma}_j^2 \eta_k^T (\tilde{A}_{i,1}^j)^T P_{i+1} (\tilde{A}_{i,1}^j) \eta_k \\
&\quad + \eta_k^T (\tilde{A}_{i,2} + \tilde{A}_{i,3})^T P_{i+1} (\tilde{A}_{i,2} + \tilde{A}_{i,3}) \eta_k \\
&\quad + \eta_{k-\tau_k}^T \tilde{A}_{d1}^T P_{i+1} \tilde{A}_{d1} \eta_{k-\tau_k} + \vartheta_k^T \tilde{D}_{i,1}^T P_{i+1} \tilde{D}_{i,1} \vartheta_k \\
&\quad + \left(\sum_{d=1}^{\infty} \mu_d \eta_{k-d}\right)^T \tilde{A}_{d2}^T P_{i+1} \tilde{A}_{d2} \left(\sum_{d=1}^{\infty} \mu_d \eta_{k-d}\right) \\
&\quad + 2\eta_k^T (\tilde{A}_{i,2} + \tilde{A}_{i,3})^T P_{i+1} \tilde{A}_{d1} \eta_{k-\tau_k} \\
&\quad + 2\eta_k^T (\tilde{A}_{i,2} + \tilde{A}_{i,3})^T P_{i+1} \tilde{A}_{d2} \left(\sum_{d=1}^{\infty} \mu_d \eta_{k-d}\right) \\
&\quad + 2\eta_k^T (\tilde{A}_{i,2} + \tilde{A}_{i,3})^T P_{i+1} \tilde{D}_{i,1} \vartheta_k \\
&\quad + 2\eta_{k-\tau_k}^T \tilde{A}_{d1}^T P_{i+1} \tilde{A}_{d2} \left(\sum_{d=1}^{\infty} \mu_d \eta_{k-d}\right) \\
&\quad + 2\eta_{k-\tau_k}^T \tilde{A}_{d1}^T P_{i+1} \tilde{D}_{i,1} \vartheta_k - \eta_k^T P_i \eta_k \\
&\quad + 2\left(\sum_{d=1}^{\infty} \mu_d \eta_{k-d}\right)^T \tilde{A}_{d2}^T P_{i+1} \tilde{D}_{i,1} \vartheta_k.
\end{aligned}$$

Furthermore, according to Lemma 1, it can be easily seen that

$$\begin{aligned}
&-\sum_{d=1}^{\infty} \mu_d \eta_{k-d}^T R \eta_{k-d} \\
&\qquad \leq -\frac{1}{\bar{\mu}} \left(\sum_{d=1}^{\infty} \mu_d \eta_{k-d}\right)^T R \left(\sum_{d=1}^{\infty} \mu_d \eta_{k-d}\right),
\end{aligned} \tag{18}$$

where $\bar{\mu}$ is defined in (2). Then, we can obtain

$$\begin{aligned}
&\mathbb{E}\left\{\Delta V_{3,k}\right\} \\
&\leq \bar{\mu} \eta_k^T R \eta_k - \frac{1}{\bar{\mu}} \left(\sum_{d=1}^{\infty} \mu_d \eta_{k-d}\right)^T R \left(\sum_{d=1}^{\infty} \mu_d \eta_{k-d}\right).
\end{aligned} \tag{19}$$

For convenience, we define the following notations:

$$\begin{aligned}
\zeta_k &= \left[\eta_k^T \quad \eta_{k-\tau_m}^T \quad \eta_{k-\tau_k}^T \quad \eta_{k-\tau_M}^T \quad \left(\textstyle\sum_{d=1}^{\infty} \mu_d \eta_{k-d}\right)^T\right]^T, \\
\xi_k &= \left[\zeta_k^T \quad \vartheta_k^T\right]^T.
\end{aligned}$$

Now, we are ready to prove the asymptotic stability in the mean-square sense of the system (9) with $\vartheta_k = 0$. Obviously, the combination of (15)-(19) results in

$$\mathbb{E}\{\Delta V_k\} \leq \mathbb{E}\{\zeta_k^T \Xi^i \zeta_k\}, \tag{20}$$

where

$$\Xi^i = \begin{bmatrix} \Xi_{11}^i & * & * & * & * \\ 0 & -Q_1 & * & * & * \\ \Xi_{31}^i & 0 & \Xi_{33}^i & * & * \\ 0 & 0 & 0 & -Q_3 & * \\ \Xi_{51}^i & 0 & \Xi_{53}^i & 0 & \Xi_{55}^i \end{bmatrix}.$$

It follows immediately from (12) that $\Xi^i < 0$. Then, from the Lyapunov stability theorem, it is easy to find that the asymptotic stability in the mean-square sense of system (9) can be confirmed when $\vartheta_k = 0$.

Next, we will analyze the H_∞ performance of the system (9) with $\vartheta_k \neq 0$ under the zero-initial condition. We consider the following index:

$$\begin{aligned} J_N &= \mathbb{E}\left\{\sum_{k=0}^{N}\left[\bar{r}_k^T \bar{r}_k - \gamma^2 \vartheta_k^T \vartheta_k\right]\right\} \\ &= \mathbb{E}\left\{\sum_{k=0}^{N}\left[\bar{r}_k^T \bar{r}_k - \gamma^2 \vartheta_k^T \vartheta_k + \Delta V_k\right]\right\} - \mathbb{E}\{V_{N+1}\} \\ &\leq \mathbb{E}\left\{\sum_{k=0}^{N}\left[\bar{r}_k^T \bar{r}_k - \gamma^2 \vartheta_k^T \vartheta_k + \Delta V_k\right]\right\} \\ &= \sum_{k=0}^{N} \xi_k^T \hat{\Xi}^i \xi_k, \end{aligned} \tag{21}$$

where $\hat{\Xi}^i$ is defined in (12). According to the previous analysis and (12), we can derive that $J_N \leq 0$. Letting $N \to \infty$, it is easy to see that

$$\sum_{k=0}^{\infty} \mathbb{E}\left\{\| \bar{r}_k \|^2\right\} \leq \gamma^2 \sum_{k=0}^{\infty} \mathbb{E}\left\{\| \vartheta_k \|^2\right\}, \tag{22}$$

which is equivalent to (10). Thus, the proof of Theorem 1 is complete.

Remark 4: In Theorem 1, the asymptotically mean-square stability with satisfactory H_∞ performance of the resulted filtering error system can be guaranteed when the fault detection filter parameters is given. In the following Theorem, we provide a sufficient condition in terms of linear matrix inequality technique that can be readily solved by Matlab software. Thus, the explicit expression of the proposed fault detection filter parameters can be derived.

Theorem 2: For given positive scalars τ_m, τ_M and a prescribed H_∞ index $\gamma > 0$, the error dynamics system (9) with $\vartheta_k = 0$ is asymptotically stable in the mean-square sense and satisfies (10) under the zero-initial condition for all nonzero ϑ_k, if there exist symmetric positive definite matrices P_i ($i = 1, 2, \cdots, m$), Q_1, Q_2, Q_3 and R, positive scalar ρ, any appropriate dimensional matrices X_i and $K_{i,2}$ ($i = 1, 2, \cdots, m$) satisfying

$$\tilde{\Xi}^i = \begin{bmatrix} \Theta_{11}^i & * \\ \Theta_{21}^i & \Theta_{22} \end{bmatrix} < 0, \tag{23}$$

where

$$\begin{aligned}
\Theta_{11}^i &= \begin{bmatrix} \Psi^i & * & * & * & * \\ \tilde{\Xi}_{21}^i + \Upsilon_{21}^i & -P_{i+1} & * & * & * \\ \tilde{\Xi}_{31}^i + \Upsilon_{31}^i & 0 & -I & * & * \\ \tilde{\Xi}_{41}^i & 0 & 0 & -P_{i+1} & * \\ \tilde{\Xi}_{51}^i & 0 & 0 & 0 & -I \end{bmatrix}, \\
\Theta_{21}^i &= \begin{bmatrix} 0 & \tilde{\Xi}_{62}^i & \hat{\Phi}_{i,2}^T K_{i,2}^T & 0 & 0 \\ \rho \check{\Lambda}_1 & 0 & 0 & 0 & 0 \end{bmatrix}, \\
\Theta_{22} &= \begin{bmatrix} -\rho I & * \\ 0 & -\rho I \end{bmatrix}, \\
\Psi^i &= \mathrm{diag}\{-P_i + Q_1 + (\tau_M - \tau_m + 1)Q_2 + Q_3 \\
&\quad + \bar{\mu}R, -Q_1, -Q_2, -Q_3, -\frac{1}{\bar{\mu}}R, -\gamma^2 I\}, \\
\tilde{\Xi}_{21}^i &= [P_{i+1}\hat{A}_{i,2} + X_i\hat{C}_{i,2}\ 0\ P_{i+1}\tilde{A}_{d1}\ 0 \\
&\quad P_{i+1}\tilde{A}_{d2}\ \ P_{i+1}\hat{D}_{i,1} + X_i\hat{D}_{i,2}], \\
\tilde{\Xi}_{31}^i &= \left[K_{i,2}\hat{C}_{i,2}\ 0\ 0\ 0\ 0\ K_{i,2}\hat{D}_{i,2} - \hat{E}^T\right], \\
\tilde{\Xi}_{41}^i &= \left[P_{i+1}\hat{A}_{i,1}^j + X_i\hat{C}_{i,1}^j\ 0\ 0\ 0\ 0\ 0\right], \\
\tilde{\Xi}_{51}^i &= \left[K_{i,2}\hat{C}_{i,1}^j\ 0\ 0\ 0\ 0\ 0\right], \\
\tilde{\Xi}_{62}^i &= \hat{\Phi}_{i,1}^T P_{i+1} + \hat{\Phi}_{i,2}^T X_i^T, \\
\check{\Lambda}_1 &= \left[\hat{\Lambda}_1\ 0\ 0\ 0\ 0\ 0\right], \\
\Upsilon_{21}^i &= \left[P_{i+1}\Sigma_{i,1} + X_i\Sigma_{i,2}\ 0\ 0\ 0\ 0\ 0\right], \\
\Upsilon_{31}^i &= \left[K_{i,2}\Sigma_{i,2}\ 0\ 0\ 0\ 0\ 0\right], \\
\hat{A}_{i,1}^j &= \begin{bmatrix} \sum_{j=1}^m \bar{\sigma}_j(\bar{A}_{i,1}^j) & 0 \\ 0 & 0 \end{bmatrix},\ \hat{A}_{i,2} = \begin{bmatrix} \bar{A}_{i,2} & 0 \\ 0 & 0 \end{bmatrix}, \\
\hat{A}_{i,3} &= \begin{bmatrix} \bar{A}_{i,3} & 0 \\ 0 & 0 \end{bmatrix},\ \hat{C}_{i,1}^j = \begin{bmatrix} 0 & 0 \\ \sum_{j=1}^m \bar{\sigma}_j(\bar{C}_{i,1}^j) & 0 \end{bmatrix}, \\
\hat{C}_{i,2} &= \begin{bmatrix} 0 & I \\ \bar{C}_{i,2} & 0 \end{bmatrix},\ \hat{C}_{i,3} = \begin{bmatrix} 0 & 0 \\ \bar{C}_{i,3} & 0 \end{bmatrix},\ \hat{D}_{i,1} = \begin{bmatrix} \bar{D}_i & \bar{G} \\ 0 & 0 \end{bmatrix}, \\
\hat{D}_{i,2} &= \begin{bmatrix} 0 & 0 \\ \Phi_i D_2 & 0 \end{bmatrix},\ \hat{E} = \begin{bmatrix} 0 \\ I \end{bmatrix},\ \hat{\Phi}_{i,1} = \begin{bmatrix} \bar{\Phi}_{i,1} \\ 0 \end{bmatrix}, \\
\bar{\Phi}_{i,1} &= \begin{bmatrix} 0 \\ \Phi_i \end{bmatrix},\ \hat{\Phi}_{i,2} = \begin{bmatrix} 0 \\ \Phi_i \end{bmatrix},\ \hat{\Lambda}_1 = \left[\bar{\Lambda}_1\ 0\right], \\
\bar{\Lambda}_1 &= \left[\Lambda_1 C\ 0\right],\ \Sigma_{i,1} = \begin{bmatrix} \Omega_{i,1} & 0 \\ 0 & 0 \end{bmatrix},\ \Sigma_{i,2} = \begin{bmatrix} 0 & 0 \\ \Omega_{i,2} & 0 \end{bmatrix}, \\
\Omega_{i,1} &= \begin{bmatrix} 0 & 0 \\ \Phi_i \bar{\Lambda} C & 0 \end{bmatrix},\ \Omega_{i,2} = \left[\Phi_i \bar{\Lambda} C\ 0\right],
\end{aligned} \tag{24}$$

with $P_{m+i} = P_i$ for all $i \in \{1, 2, \cdots, m\}$. Furthermore, the filter parameters in the form of (8) are given as follows:

$$\begin{aligned} \left[\bar{A}_{i,F}\ \bar{B}_{i,F}\right] &= (\hat{E}^T P_{i+1} \hat{E})^{-1} \hat{E}^T X_i, \\ \left[\bar{D}_{i,F}\ \bar{E}_{i,F}\right] &= K_{i,2}. \end{aligned} \tag{25}$$

Proof: First, we rewrite the parameters in Theorem 1 as the following form:

$$\begin{aligned}\sum_{j=1}^{m}\bar{\sigma}_j(\tilde{A}^j_{i,1}) &= \hat{A}^j_{i,1}+\hat{E}K_{i,1}\hat{C}^j_{i,1},\\ \tilde{A}_{i,2} &= \hat{A}_{i,2}+\hat{E}K_{i,1}\hat{C}_{i,2},\\ \tilde{A}_{i,3} &= \hat{A}_{i,3}+\hat{E}K_{i,1}\hat{C}_{i,3},\\ \sum_{j=1}^{m}\bar{\sigma}_j(\tilde{C}^j_{i,1}) &= K_{i,2}\hat{C}^j_{i,1},\\ \tilde{C}_{i,2} &= K_{i,2}\hat{C}_{i,2},\quad \tilde{C}_{i,3}=K_{i,2}\hat{C}_{i,3},\\ \tilde{D}_{i,1} &= \hat{D}_{i,1}+\hat{E}K_{i,1}\hat{D}_{i,2},\\ \tilde{D}_{i,2} &= K_{i,2}\hat{D}_{i,2}-\hat{E}^T,\\ K_{i,1} &= \begin{bmatrix}\bar{A}_{i,F} & \bar{B}_{i,F}\end{bmatrix}.\end{aligned} \tag{26}$$

By using Lemma 2 and (26), (12) can be rewritten as

$$\begin{bmatrix}\Psi^i & * & * & * & *\\ \breve{\Xi}^i_{21} & -P^{-1}_{i+1} & * & * & *\\ \breve{\Xi}^i_{31} & 0 & -I & * & *\\ \breve{\Xi}^i_{41} & 0 & 0 & -P^{-1}_{i+1} & *\\ \breve{\Xi}^i_{51} & 0 & 0 & 0 & -I\end{bmatrix}<0, \tag{27}$$

where

$$\begin{aligned}\breve{\Xi}^i_{21} &= \big[\hat{A}_{i,2}+\hat{E}K_{i,1}\hat{C}_{i,2}+\hat{A}_{i,3}+\hat{E}K_{i,1}\hat{C}_{i,3}\quad 0\quad \tilde{A}_{d1}\\ &\qquad 0\quad \tilde{A}_{d2}\quad \hat{D}_{i,1}+\hat{E}K_{i,1}\hat{D}_{i,2}\big],\\ \breve{\Xi}^i_{31} &= \big[K_{i,2}\hat{C}_{i,2}+K_{i,2}\hat{C}_{i,3}\ 0\ 0\ 0\ 0\ K_{i,2}\hat{D}_{i,2}-\hat{E}^T\big],\\ \breve{\Xi}^i_{41} &= \big[\hat{A}^j_{i,1}+\hat{E}K_{i,1}\hat{C}^j_{i,1}\ 0\ 0\ 0\ 0\ 0\big].\end{aligned}$$

Pre- and post-multiplying the (27) by $\mathrm{diag}\{I, P_{i+1}, I, P_{i+1}, I\}$ and defining $X_i = P_{i+1}\hat{E}K_{i,1}$, we can directly derive that

$$\begin{bmatrix}\Psi^i & * & * & * & *\\ \tilde{\Xi}^i_{21}+\breve{\Upsilon}^i_{21} & -P_{i+1} & * & * & *\\ \tilde{\Xi}^i_{31}+\breve{\Upsilon}^i_{31} & 0 & -I & * & *\\ \tilde{\Xi}^i_{41} & 0 & 0 & -P_{i+1} & *\\ \tilde{\Xi}^i_{51} & 0 & 0 & 0 & -I\end{bmatrix}<0, \tag{28}$$

where

$$\begin{aligned}\breve{\Upsilon}^i_{21} &= \big[P_{i+1}\hat{A}_{i,3}+X_i\hat{C}_{i,3}\quad 0\quad 0\quad 0\quad 0\quad 0\big],\\ \breve{\Upsilon}^i_{31} &= \big[K_{i,2}\hat{C}_{i,3}\quad 0\quad 0\quad 0\quad 0\quad 0\big].\end{aligned}$$

We are now in a position to deal with the system subject to uncertainties described in (6). Let us use $\bar{\Lambda}+\Gamma\Lambda_1$ replace $\bar{\Lambda}$ in $\hat{A}_{i,3}$ and $\hat{C}_{i,3}$. According to (28), we can get

$$\Theta^i_{11}+\tilde{H}_i\Gamma\tilde{\Lambda}_1+(\tilde{H}_i\Gamma\tilde{\Lambda}_1)^T<0, \tag{29}$$

where

$$\begin{aligned}\tilde{H}_i &= \Big[0\ (P_{i+1}\hat{\Phi}_{i,1}+X_i\hat{\Phi}_{i,2})^T\ \ \hat{\Phi}^T_{i,2}K^T_{i,2}\ 0\ 0\Big]^T,\\ \tilde{\Lambda}_1 &= \big[\check{\Lambda}_1\ 0\ 0\ 0\ 0\big].\end{aligned}$$

Here, Θ^i_{11}, $\hat{\Phi}_{i,1}$, $\hat{\Phi}_{i,2}$ and $\check{\Lambda}_1$ are defined in (24).

Based on Lemma 3, we can easily obtain that (29) holds if and only if there exists a positive scalar ρ such that

$$\Theta^i_{11}+\rho^{-1}\tilde{H}_i\tilde{H}_i^T+\rho\tilde{\Lambda}_1^T\tilde{\Lambda}_1<0. \tag{30}$$

According to Lemma 2 and (23) yield (30), which ends the proof.

Remark 5: Up to now, we have studied the protocol-based fault detection problem for discrete system with mixed time-delays and missing measurements, where the missing probabilities could be uncertain. It should be noted that the protocol-dependent Lyapunov functional has been constructed in (14) with hope to better depict the characteristic of RR protocol. Based on the Lyapunov stability theorem, new probability-dependent sufficient conditions have been proposed to guarantee that the error dynamics system is asymptotically stable in the mean-square sense and satisfies H_∞ performance. Moreover, the concrete expression of the filter gains has been given.

IV. A NUMERICAL EXAMPLE

In this section, a numerical simulation example is given to demonstrate the effectiveness of the proposed fault detection approach.

Example 1: Consider the discrete delayed system (1) subject to missing measurements with the following system parameters:

$$\begin{aligned}A &= \begin{bmatrix}0.6 & 0.2\\ 0 & 0.7\end{bmatrix},\quad A_{d1}=\begin{bmatrix}0.03 & 0\\ 0.02 & 0.03\end{bmatrix},\\ A_{d2} &= \begin{bmatrix}0.01 & 0\\ 0 & 0.01\end{bmatrix},\quad D_1=\begin{bmatrix}0.8\\ 0.3\end{bmatrix},\quad G=\begin{bmatrix}-1\\ 0.6\end{bmatrix},\\ C &= \begin{bmatrix}0.2 & -0.1\\ 0.3 & -0.2\end{bmatrix},\quad D_2=\begin{bmatrix}0.6\\ 0.7\end{bmatrix}.\end{aligned}$$

Let the time-varying delays satisfy $1\le\tau_k\le 3$ and assume that $\bar{\lambda}_i=0.9$, $\epsilon_i=0.05$ $(i=1,2)$. Choosing the constant $\mu_d=2^{-3-d}$, we have $\bar{\mu}=\sum_{d=1}^{\infty}\mu_d=2^{-3}<\sum_{d=1}^{\infty}d\mu_d=2^{-2}<+\infty$, which satisfies the convergence condition in (2). Let the performance index given in (10) be $\gamma=1.4$.

According to Theorem 2, the fault detection filter parameters can be gained as follows:

$$\begin{aligned}\bar{A}_{1,F} &= \begin{bmatrix}0.0066 & 0.0160 & 0.0017 & -0.0020\\ 0.0012 & 0.319 & -0.0014 & 0.0017\\ 0.0006 & 0.0006 & 0.0002 & -0.0003\\ -0.0007 & -0.0007 & -0.0002 & 0.0002\end{bmatrix},\\ \bar{B}_{1,F} &= \begin{bmatrix}-0.0011 & 0.0003\\ -0.0001 & 0.0002\\ -0.1623 & -0.0225\\ -0.0225 & -0.1552\end{bmatrix},\\ \bar{D}_{1,F} &= \begin{bmatrix}-2.6302 & -0.7613 & -0.9010 & 1.0561\end{bmatrix},\\ \bar{E}_{1,F} &= \begin{bmatrix}-0.0619 & 0.0281\end{bmatrix},\end{aligned}$$

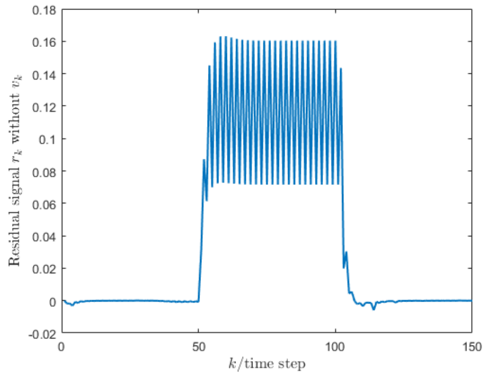

FIGURE 2. Residual signal r_k without v_k.

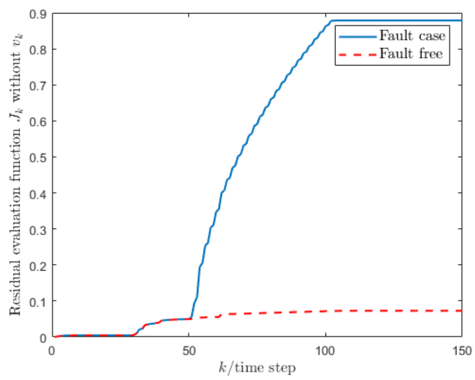

FIGURE 3. Evolution of residual evaluation function J_k without v_k.

$$\bar{A}_{2,F} = \begin{bmatrix} 0.0098 & 0.0169 & -0.0001 & 0.0001 \\ 0.0074 & 0.0300 & 0.0002 & -0.0001 \\ -0.0025 & 0.0047 & 0.0001 & -0.0001 \\ 0.0029 & -0.0054 & -0.0001 & 0.0002 \end{bmatrix},$$

$$\bar{B}_{2,F} = \begin{bmatrix} -0.0001 & -0.0005 \\ 0.0003 & 0.0001 \\ -0.1050 & -0.0895 \\ -0.0893 & -0.0771 \end{bmatrix},$$

$$\bar{D}_{2,F} = \begin{bmatrix} -4.1794 & 1.7205 & 0.1026 & -0.1170 \end{bmatrix},$$

$$\bar{E}_{2,F} = \begin{bmatrix} 0.0128 & -0.0750 \end{bmatrix}.$$

We assume the initial conditions as $\bar{x}_0 = [\,0.2\ \ -0.3\ \ 0.2\ \ 0.1\,]^T$ and $\hat{\bar{x}}_0 = [\,0\ \ 0\ \ 0\ \ 0\,]^T$. In order to further elaborate the effectiveness of the designed fault detection filter, for $k = 0, 1, \cdots, 150$, let the fault signal f_k be given by:

$$f_k = \begin{cases} 1, & 50 \le k \le 100 \\ 0, & \text{else} \end{cases}$$

On one hand, in the case that the external disturbance $v_k = 0$, the residual signal r_k and evolution of residual evaluation function J_k are depicted in Figs. 2 and 3, respectively, which imply that the filter designed in this paper can effectively detect the faults when it occurs. On the other hand, suppose

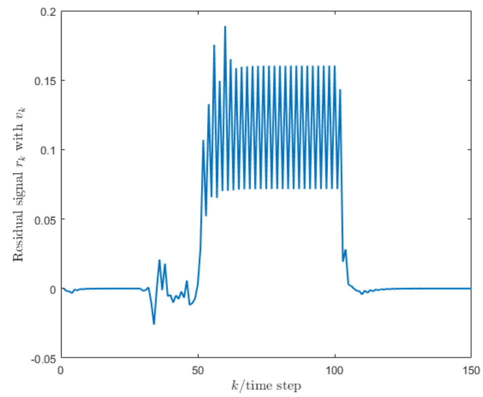

FIGURE 4. Residual signal r_k with v_k.

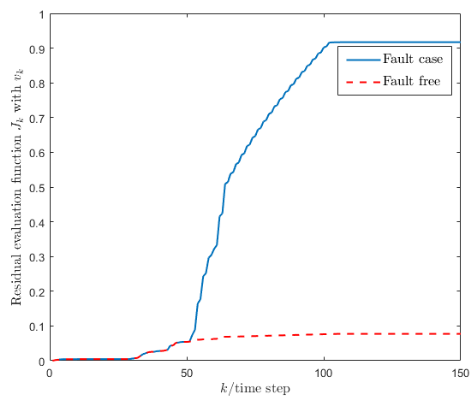

FIGURE 5. Evolution of residual evaluation function J_k with v_k.

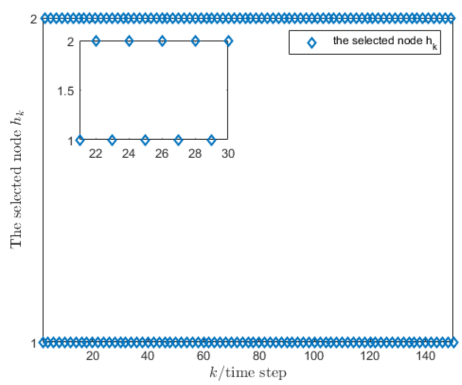

FIGURE 6. The selected node h_k.

that the disturbance is given by

$$v_k = \begin{cases} 0.2 \times \text{rand}[0,1], & 30 \le k \le 60 \\ 0, & \text{else} \end{cases}$$

where the rand[0, 1] represents the arrays of random numbers whose elements are uniformly distributed over the interval [0, 1]. The residual signal r_k and evolution of residual evaluation function J_k are plotted in Figs. 4 and 5, respectively. The threshold can be chosen as $J_{th} = \sup_{f=0} \mathbb{E}\{\sum_{l=0}^{150} r_l^T r_l\}^{1/2}$. After running the simulation 100 times, we get the average value of $J_{th} = 0.0748$. According to Fig. 5, it is easy to find that $0.0737 = J(52) < J_{th} < J(53) = 0.0891$, which indicates that the fault can be detected in 3 time steps after its occurrence. Furthermore, the selected node at each transmission step under the RR protocol is shown in Fig. 6. It is straightforward to see from Fig. 6 that under the RR protocol, only one node can transmit the data at each transmission time.

V. CONCLUSION

In this paper, we have investigated the protocol-based fault detection problem for discrete systems subject to mixed time-delays and missing measurements under uncertain missing probabilities, where the uncertain missing probabilities of missing measurements have been characterized and the RR protocol has been utilized to save the communication resources. By utilizing the Lyapunov approach, some sufficient conditions have been obtained in terms of certain LMIs, which ensure that the error dynamics system is asymptotically stable in the mean-square sense and satisfies H_∞ performance. Furthermore, the specific expression of the desired filter gains has been presented. Finally, a numerical simulation example has been given to show the effectiveness of the proposed fault detection filtering method. Further research topics based on the proposed results include the designs of fault detection filters for networked systems with different transmission protocols (e.g. stochastic communication protocol, the weighted try-once-discard protocol) or dynamic event-triggered scheme.

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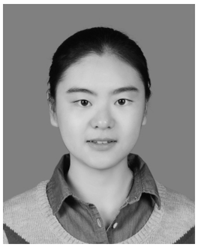

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