A FAULT DIAGNOSIS METHOD BASED ON ZONOTOPES

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Abstract. In this paper, zonotope theory is used to address the problem of detecting faults in technical systems described by discrete-time dynamic linear models with exogenous disturbances and measurement noise. To construct the corresponding zonotope, a reduced (lower-dimensional) model of the original system is developed; this model is insensitive to exogenous disturbances. To simplify the solution procedure, the matrices of the reduced model are written in the identification canonical form, which also ensures model stability. Based on this form, an equation is derived to find a solution of minimal dimension. If the insensitivity to exogenous disturbances cannot be achieved, a minimum sensitivity solution is obtained. Based on the resulting model, a diagnostic observer is designed that generates a residual for deciding on the presence/absence of faults. The observer design formulas are used to construct a fault-detecting zonotope. The theoretical framework is illustrated with a practical problem of detecting faults in an electric drive of an underwater vehicle as an example. According to the simulation results in MATLAB, the theoretical framework is correct.

Keywords: discrete systems, faults, diagnostic observers, residual, disturbances, measurement noise, zonotopes.

INTRODUCTION

Modern technical systems often perform critical functions; therefore, it is highly desirable to continuously check the correct functioning of such systems during definite operations in order to detect faults that could violate them. Such checking is usually realized via the so-called diagnostic observers, which are software-implemented reduced models of the systems under consideration.

The signal generated by such an observer is compared with the readings from system sensors; the difference between these signals, called the residual, serves as an indicator of the system's correct functioning. Ideally, when there are no exogenous disturbances or measurement noise, zero residual means correct functioning (no faults) whereas a nonzero value testifies to the presence of faults.

Real systems always contain exogenous disturbances and measurement noise, so the residual is never zero even without faults. In this case, an adaptive threshold is often used to reduce the number of incorrect diagnostic decisions: the residual signal is compared with this threshold. However, forming such a threshold is a challenge. In recent years, it has been addressed by using the so-called interval observers, originally developed to estimate the state vector of many classes of systems: continuous-time linear [1, 2], discrete-time linear [1, 3], and nonlinear [4, 5]. In [3, 6, 7], such observers were characterized by reduced dimension. In [8–10], they were used to solve the fault diagnosis problem as follows: two residual signals are generated instead of a single one so that, in the absence of faults, the values of one signal are greater than or equal to zero, and those of the other are less than or equal to zero; if zero lies between the residuals, then the system is decided to have no faults (and a fault is decided to occur otherwise). Unlike an adaptive threshold, the residual values are independent of control, which simplifies the diagnostic procedure.

In addition to interval observers, the so-called zonotopes have been actively applied in recent years to solve such problems. Zonotopes are convex solids in a multidimensional space. They were built for linear discrete-time systems with constant parameters [11–14], systems with variable parameters [15], and nonlinear systems [16–18]. The zonotope-based solution to the fault detection problem presented in [15] is as follows. Let the center of a zonotope and the matrices generating it be determined based on a diagnostic observer and its residual. A decision regarding faults is made by analogy with an interval observer: if the zonotope includes zero, then there are no faults (and a fault occurs otherwise).

Thus, zonotopes are similar to interval observers but are characterized by greater capabilities for considering disturbances and measurement noise, in particular, their potential correlation. In this paper, we develop a novel method for constructing zonotopes to solve the fault diagnosis problem of discrete-time systems. Unlike the works [11–18], where zonotopes were constructed based on the original system, the novel method involves a reduced (lower-dimensional) model of the system. Due to the lower dimension of the model, the dimension of the zonotope's space is also reduced, which decreases the number of operations required to determine its characteristics; and since all such operations are carried out in real time, the computational complexity of the diagnostic procedure is lowered as well. Furthermore, by using a reduced model, in some cases, it is possible to eliminate the impact of exogenous disturbances on the diagnostic procedure and decrease the probability of wrong decisions.

1. BASIC CONCEPTS AND MODELS

For a given integer $s \ge n$, with n denoting the dimension of a system, and a hypercube $\mathrm{B}^s = [-1,\ 1]^s \in R^s$, a zonotope is defined as

$$Z = \langle c, P \rangle = c + P\mathrm{B}^s = \{z \in R^n : z = c + Pb,\ \ b \in \mathrm{B}^s\},$$

where $c \in R^n$ is the zonotope's center; $P \in R^{n \times s}$ is the generating matrix that determines its shape and volume [11, 12]. A zonotope has several properties, described in detail in [11, 12]; they will not be required below. Like a hypercube, a zonotope is a convex solid, but it can have a more complex shape. The number s is called the zonotope's order.

The system under consideration is described by the discrete-time linear model

$$\begin{aligned} x(t+1) &= Fx(t) + Gu(t) + Lw(t) + Dd(t), \\ y(t) &= Hx(t) + v(t), \end{aligned} \qquad (1)$$

where $x(t) \in R^n$, $y(t) \in R^l$, and $u(t) \in R^m$ are the state, output, and control vectors, respectively; $F \in R^{n \times n}$, $G \in R^{n \times m}$, $L \in R^{n \times n_2}$, $D \in R^{n \times p}$, and $H \in R^{l \times n}$ are constant matrices of compatible dimensions; $w(t) \in R^{n_2}$ are exogenous disturbances described by a zonotope $W = \langle 0, P_w \rangle$ of order s_3; $v(t) \in R^l$ are measurement noises described by a zonotope $V = \langle 0, P_v \rangle$ of order s_2; finally, a function $d(t) \in R^p$ describes the fault. By assumption, the initial state $x(0)$ is unknown but bounded by a zonotope $Z_x = \langle c_x(0), P_x(0) \rangle$ of order s_1. In addition, the exogenous disturbances $w(t)$ and measurement noise $v(t)$ are supposed to be random, and the fault $d(t)$ is supposed to be deterministic; no restrictions are imposed on the distribution laws of the random processes $w(t)$ and $v(t)$ (other than those determined by their zonotopes).

Under the above assumptions, the problem is to design a diagnostic observer for deciding on the presence/absence of faults in the system. To solve this problem, we build a disturbance-insensitive model of the form

$$\begin{aligned} x_*(t+1) &= F_* x_*(t) + J_* y(t) + G_* u(t) + D_* d(t), \\ y_*(t) &= H_* x_*(t) = R_* y(t), \end{aligned} \qquad (2)$$

where $x_* \in R^k$ is the state vector of the model; k is its dimension; J_* and G_* are constant matrices to be determined; the matrices H_* and F_* are specified in the identification canonical form

$$F_* = \begin{pmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 \\ \cdots & \cdots & \cdots & \ddots & \cdots \\ 0 & 0 & 0 & \cdots & 0 \end{pmatrix}, \quad H_* = (1 \quad 0 \quad \ldots \quad 0), \qquad (3)$$

which ensures the stability of this model. The other matrices are determined from the equation [19, 20]

$$(R_* \quad -J_{*1} \quad \ldots \quad -J_{*k})(W^{(k)} \quad L_*^{(k)}) = 0, \qquad (4)$$

$$W^{(k)} = \begin{pmatrix} HF^k \\ HF^{k-1} \\ \vdots \\ H \end{pmatrix},$$

$$L_*^{(k)} = \begin{pmatrix} HL & HFL & \ldots & HF^{k-1}L \\ 0 & HL & \ldots & HF^{k-2}L \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & 0 \end{pmatrix}, \quad k = 1, 2, \ldots,$$

which has a nontrivial solution if

$$\operatorname{rank}(V^{(k)} \quad L^{(k)}) < l(k+1). \tag{5}$$

By assumption, the vectors $x(t)$ and $x_*(t)$ are related by the matrix Φ (to be determined as well):

$$x_*(t) = \Phi x(t).$$

As is known [19, 20], the model matrices satisfy the equations

$$\Phi F = F_*\Phi + J_*H,\ R_*H = H_*\Phi,\ G_* = \Phi G,$$

$$L_* = \Phi L = 0,\ D_* = \Phi D. \tag{6}$$

To build the model, one should proceed as follows: verify condition (5) and select the minimum value of k, starting from $k=1$; determine the row $(R_* \quad -J_{*1} \quad \ldots \quad -J_{*k})$ from equation (4); and finally, based on the relations

$$\Phi_1 = R_*H,\ \Phi_i F = \Phi_{i+1} + J_{*i}H,\ i = \overline{1, k-1},$$

$$\Phi_k F = J_k H,$$

obtained due to the form (3), construct the matrix Φ, and determine the matrices G_* and D_* from equations (6). If condition (5) fails, another solution of equation (4) should be found. If condition (5) does not hold for all $k < n$, then a robust solution minimizing the disturbance's contribution to the model should be found; for details, see [20].

2. CONSTRUCTION OF A DIAGNOSTIC ZONOTOPE

To solve the problem, based on model (2), we introduce a diagnostic observer that generates the residual $r(t)$ for deciding on fault occurrence:

$$\begin{aligned} &\hat{x}_*(t+1) = F_*\hat{x}_*(t) + G_*u(t) + J_*y(t),\\ &\hat{y}_*(t) = H_*\hat{x}(t),\\ &r(t) = R_*y(t) - \hat{y}_*(t). \end{aligned} \tag{7}$$

In contrast to model (2), which actually represents a virtual object within system (1) that is insensitive to disturbances, the diagnostic observer exists in reality and generates the residual. Diagnostic decisions are made based on a zonotope of the following structure.

Theorem. *If $d(t) = 0$, then the residual belongs to a zonotope of the form $Z_r(t) = \langle c_r(t), P_r(t)\rangle$, where*

$$c_r(t) = 0,\ P_r(t) = [H_*P_*(t) \quad R_*P_v]. \tag{8}$$

P r o o f. Let the variable $\hat{x}_*(t)$ belong to the zonotope $Z_*(t) = \langle c_*(t), P_*(t)\rangle$ of order s_1, i.e.,

$$\hat{x}_*(t) = c_*(t) + P_*(t)b_1,\ b_1 \in \mathrm{B}^{s_1}. \tag{9}$$

In view of equation (7), we obtain

$$\hat{x}_*(t+1) = F_*c_*(t) + G_*u(t) + J_*y(t) + F_*P_*(t)b_1.$$

Since the variable $y(t)$ is corrupted by the measurement noise, it belongs to a zonotope of order s_2 with a center $Hc_x(t)$ and a generating matrix P_v:

$$y(t) = Hc_x(t) + P_v b_2,\ b_2 \in \mathrm{B}^{s_2}, \tag{10}$$

where $c_x(t)$ is the center of the zonotope for $x(t)$.

Taking into account equations (9), (10), and $R_*H = H_*\Phi$, we transform the expression for the residual in the absence of faults. By the stability of the diagnostic observer, its states and those of system (1) become consistent with each other after the transients, i.e., $c_*(t) = \Phi c_x(t)$. As a result, we have

$$\begin{aligned} r(t) &= R_*y(t) - H_*\hat{x}_*(t)\\ &= R_*(Hc_x(t) + P_v b_2) - H_*(c_*(t) + P_*(t)b_1)\\ &= H_*\Phi c_x(t) + R_*P_v b_2 - (H_*\Phi c_x(t) + H_*P_*(t)b_1)\\ &= -H_*P_*(t)b_1 + R_*P_v b_2. \end{aligned} \tag{11}$$

The minus sign in the first term can be omitted due to the independence of the vectors b_1 and b_2. Therefore, the residual $r(t)$ belongs to a zonotope of order $s_1 + s_2$ with center at the zero point and the generating matrix $[H_*P_*(t) \quad R_*P_v]$. ♦

When a fault occurs at a time instant $t-1$, we obtain $c_*(t) = \Phi c_x(t) + D_*d(t-1)$, the center of the zonotope $Z_r(t)$ shifts, and if the fault value exceeds a given level determined by the matrices $P_*(t)$ and P_v, the zonotope $Z_r(t)$ ceases to include zero. According to the theorem and this remark, the decisions are made as follows: if $0 \in Z_r(t)$, then there are no faults; if $0 \notin Z_r(t)$, then a fault occurs.

If the model is sensitive to the disturbances, then the matrix (5) is supplemented with the element $H_*L_*P_w$.

Let the function $d(t)$ be associated with a zonotope $Z_d = \langle 0, P_d\rangle$ in the sense of classifying $d(t) \in Z_d$ not as a fault, but as an admissible change in the system parameters. Obviously, this case corresponds to the extended matrix $P_r(t)=[H_*P_*(t)\quad R_*P_v\quad H_*D_*P_d]$.

Note that in [11–18], zonotopes were constructed based on the original system; as a result, the dimension of their space coincided with that of the system. In the novel method (proposed here), due to the lower dimension of the model, the dimension of the zonotope's space is reduced, which decreases the number of operations required to determine its characteristics, thereby lowering the computational complexity of the diagnostic procedure. Furthermore, the reduced model is insensitive to the exogenous disturbances, which decreases the probability of wrong diagnostic decisions.

3. EXAMPLE

Consider a discretized model of an electric drive [21]:

$$\begin{aligned} &x_1(t+1)=k_1x_2(t)+x_1(t),\\ &x_2(t+1)=k_2x_2(t)+k_3x_3(t)+w(t),\\ &x_3(t+1)=k_4x_2(t)+k_5x_3(t)+k_6u(t)+d(t),\\ &y_1(t)=x_1(t)+v_1(t),\quad y_2(t)=x_3(t)+v_2(t), \end{aligned} \tag{12}$$

where the variables $x_1(t)$, $x_2(t)$, and $x_3(t)$ are the speed and angle of rotation of the motor shaft and the armature current, respectively; the coefficients $k_1,\ldots,\ k_6$ represent the parameters of the electric drive and the sampling interval; the disturbance $w(t)$ is caused by an external load torque applied to the motor shaft; the fault $d(t)$ is caused by a change in the active resistance of the motor winding due to its overheating; finally, the control $u(t)$ is the voltage applied to the motor. Model (12) is described by the matrices

$$F=\begin{pmatrix}1 & k_1 & 0\\ 0 & 1 & k_2\\ 0 & k_3 & k_4\end{pmatrix},\ G=\begin{pmatrix}0\\0\\k_5\end{pmatrix},\ H=\begin{pmatrix}1 & 0 & 0\\ 0 & 0 & 1\end{pmatrix},\ L=\begin{pmatrix}0\\1\\0\end{pmatrix},$$

$$D=\begin{pmatrix}0\\0\\1\end{pmatrix},\ \text{and}\ P_v=\begin{pmatrix}v_{*1} & 0\\ 0 & v_{*2}\end{pmatrix}.$$

Equation (4) with $k=1$ yields $J_*=(k_4\quad -k_1k_5)$ and $R_*=(k_4\quad -k_1)$; as a result, we obtain $\Phi=(k_4\quad 0\quad -k_1)$, $G_*=-k_1k_6$, and $D_*=-k_1$. The diagnostic observer (7) takes the form

$$\begin{aligned} &\hat{x}_*(t+1)=k_4y_1(t)-k_1k_5y_2(t)-k_1k_6u(t)-k_1d(t),\\ &\hat{y}_*(t)=\hat{x}_*(t),\\ &r(t)=y_1(t)+y_2(t)-\hat{y}_*(t). \end{aligned} \tag{13}$$

Since $F_*=0$ and $H_*=1$, the expression (8) gives

$$P_*(t+1)=[F_*P_*(t)\quad J_*L_yP_v]$$
$$=(k_4\quad -k_1k_5)\begin{pmatrix}v_{*1} & 0\\ 0 & v_{*2}\end{pmatrix}=(k_4v_{*1}\quad -k_1k_5v_{*2}),$$

and consequently,

$$P_r(t+1)=[P_*(t)\quad R_*L_yP_v]$$
$$=(k_4v_{*1}\quad -k_1k_5v_{*2}\quad k_4v_{*1}\quad -k_1v_{*2}).$$

Since the zonotope's center is zero, by formula (11) and the independence of the vectors b_1 and b_2, its lower $\underline{r}$ and upper $\overline{r}$ bounds are –0.04 and 0.04, respectively.

Note that the zonotope constructed by the methods from [11–18] would be a three-dimensional body, in contrast to the one-dimensional one in this example. Therefore, the computational complexity of the diagnostic procedure is lowered, the time for the necessary calculations is reduced, and diagnostic decision-making is accelerated accordingly.

For simulations, we took system (12) and the diagnostic observer (13) with $u(t)=0.3\sin(t/10)$; the exogenous disturbance $w(t)$ was specified as a random variable with the uniform distribution on the interval (–0.05, 0.05); for each time instant t, the noises $v_1(t)$ and $v_2(t)$ were specified as independent random variables with the uniform distribution on the interval (–0.01, 0.01) (i.e., the corresponding zonotope $V=\langle 0, P_v\rangle$ was a square with a side length of 0.02) and $v_{1*}=v_{2*}=0.01$. For the sake of simplicity, we selected the parameters $k_1=k_2=k_3=k_6=1$ and $k_4=k_5=-1$.

The simulation results for the initial conditions $x(0)=0$, $\underline{x}_*(0)=0.2$, and $\hat{x}_*(0)=0.1$ are shown in the figure below (the dynamics of the residual $r(t)$ and its lower and upper bounds upon the occurrence of the fault

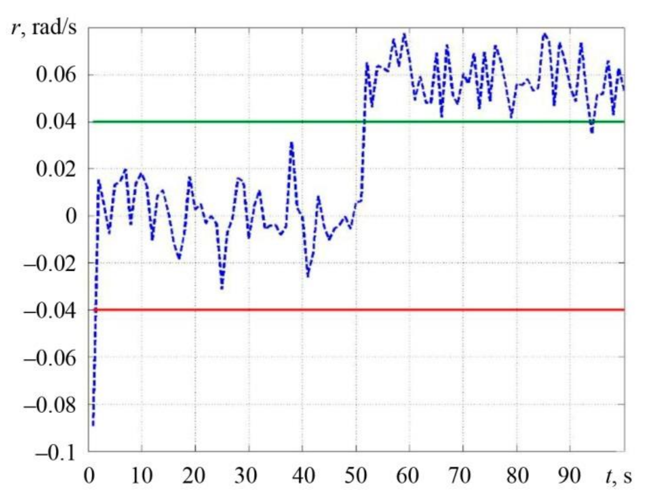

Fig. The dynamics of the residual and its lower and upper bounds upon fault occurrence.

$d = 0.06$ at the time instant $t = 50$). Obviously, the fault is reliably detected against the background of measurement noise.

CONCLUSIONS

This paper has considered the problem of diagnosing discrete linear systems under exogenous disturbances and measurement noise using zonotope theory. To solve the problem, a reduced model of the original system, insensitive to disturbances, has been developed. Based on this model, relations have been derived for constructing a zonotope capable of detecting faults in the system. Computer simulations have confirmed the correctness of the theoretical framework.

The novel method is advantageous over the existing ones as it reduces the computational complexity of the diagnostic procedure and relaxes the constraints imposed on the original system for solving the problem. Owing to the reduced model, in some cases, it is possible to even eliminate the impact of exogenous disturbances on the diagnostic process and decrease the probability of wrong decisions.

The above approach can be extended to random faults described by a deterministic zonotope. We intend to generalize this approach to nonlinear systems and to the cases where an exogenous disturbance-insensitive model cannot be constructed.

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