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Fault Detection of Nonlinear Systems Based on Time-Varying Thresholds and Neural Network Observer

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Abstract

This paper advanced a fault detection (FD) strategy based on neural network (NN) observer and a time-varying threshold for unknown nonlinear systems. Firstly, NN is applied to approximating the unknown nonlinear function and FD observer is constructed with recursive algorithm. Secondly, the time-varying thresholds are calculated with the application of the prescribed performance bound (PPB) and the FD decision is proposed. Fault detectability is analyzed simultaneously. The proposed time-varying threshold method reduces false alarms induced by overshoot within transients and alerts as early as possible compared to the method that does without considering PPB. Finally, the availability of the approach is demonstrated by the comparison result of the simulation instances.

Methodologies

Introduce the prescribed performance function, which is selected as $\varphi(t)=(\varphi_0-\varphi_\infty)e^{-\lambda t}+\varphi_\infty$. Define $e_y(t)=\varphi(t)P(\xi)$, where $\xi(t)$ is the converted residual and $P(\xi)$ is a rigorously increasing function.

The differential conversion of the residual $e_y(t)$ is shown as below:

$$\dot{\xi}(t)=\dot{e}_y(t)-\dot{\varphi}(t)P(\xi)/\varphi(t)(\partial P/\partial\xi)$$

FD observer is constructed with recursive algorithm. Define $e_i(t)=\hat{x}_i(t)-x_i(t), i=1,2,\cdots,n$ and $\tilde{W}=\hat{W}-W^*$, the error dynamics are obtained as below:

$$\begin{aligned}
\dot{e}_1(t)&=e_2(t)+N_n\Psi(\cdot)-\omega_1(t)\\
\dot{e}_2(t)&=e_3(t)+N_{n-1}\Psi(\cdot)-\omega_2(t)\\
&\vdots\\
\dot{e}_{n-1}(t)&=e_n(t)+N_2\Psi(\cdot)-\omega_{n-1}(t)\\
\dot{e}_n(t)&=\Delta a(x)+N_1\Psi(\cdot)-\omega_n(t)\\
e_y(t)&=\hat{y}(t)-y(t)
\end{aligned}$$

where $\Delta a(x)=\hat{a}(\hat{x})-a(x)=\tilde{W}^T(t)S(\hat{x})+\eta-\delta$, $\eta=W^T\tilde{S}$, η is bounded.

Using recursive algorithms to recursively obtain achievable neural network weight update laws and observer gain functions step by step. The NN weight update law is designed $\dot{\hat{W}}_1=-(e_1S_1(\hat{x})+\hat{W}_1)$, the residual generator gain functions as follow:

$$\Psi(\cdot)=-\varphi(t)(\partial P/\partial\xi)\xi(t)q_n-\dot{\varphi}(t)P(\xi)-\hat{W}_1(t)S_1(\hat{x}(t))$$

Retrospect the error conversion $e_y(t)=\varphi(t)P(\xi)$ and define $\bar{\xi}=\sqrt{\frac{G_n}{z_{n-1}}}$, it is true that $|P(\xi)|\le P(\bar{\xi})$; therefore, $|e_y(t)|\le\varphi(t)P(\bar{\xi})$.

The fault alarm is generated when $e_y(t)$ is beyond of the following threshold range: $\varphi(t)P(\bar{\xi})<e_y(t)<-\varphi(t)P(\bar{\xi})$

Mathematical Formulas

Regard the below problem of fault detection for unknown nonlinear systems:

$$\begin{aligned}
\dot{x}_1(t)&=x_2(t)+\omega_1(t)+\phi_1(t-T)g_1(\bar{x}_1(t))\\
\dot{x}_2(t)&=x_3(t)+\omega_2(t)+\phi_2(t-T)g_2(\bar{x}_2(t))\\
&\vdots\\
\dot{x}_{n-1}(t)&=x_n(t)+\omega_{n-1}(t)+\phi_{n-1}(t-T)g_{n-1}(\bar{x}_{n-1}(t))\\
\dot{x}_n(t)&=a(x)+u(t)+\omega_n(t)+\phi_n(t-T)g_n(x(t))\\
y(t)&=x_1(t)
\end{aligned}\tag{1}$$

Considering the unknown nonlinear function within the system, the NN is applied to approximating $a(x)$ as $a(x)=W^{*T}S(x)+\delta$.

Based on the NN observer, the structure of the residual generator is designed as below:

$$\begin{aligned}
\dot{\hat{x}}_1(t)&=\hat{x}_2(t)+N_n\Psi(\cdot)\\
\dot{\hat{x}}_2(t)&=\hat{x}_3(t)+N_{n-1}\Psi(\cdot)\\
&\vdots\\
\dot{\hat{x}}_{n-1}(t)&=\hat{x}_n(t)+N_2\Psi(\cdot)\\
\dot{\hat{x}}_n(t)&=\hat{a}(\hat{x})+u(t)+N_1\Psi(\cdot)\\
\hat{y}(t)&=\hat{x}_1(t)
\end{aligned}\tag{2}$$

$\hat{a}(\hat{x})$ is an online approximation model with adjustable weights as $\hat{a}(\hat{x})=\hat{W}^T(t)S(\hat{x})$.

Figures

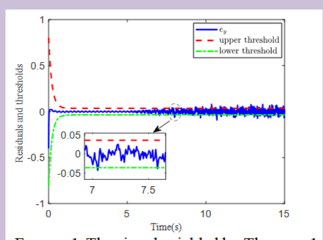

FIGURE 1. The signals yielded by Theorem 1

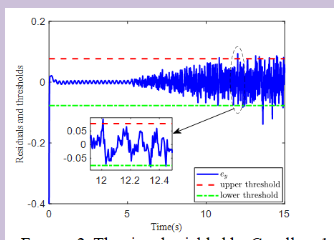

FIGURE 2. The signals yielded by Corollary 1

The results of the simulation are illustrated in Figures 1 and 2. The residual and time-varying thresholds obtained from Theorem 1 are given in Figure 1. Figure 2 illustrates the tracks of signals obtained from Corollary 1.

Conclusion

In this paper, a residual generator is constructed using the NN and recursive algorithm to ensure the residual is inside the PPB in the absence of faults. The time-varying thresholds based on the PPB can detect faults faster and reduce false alarms resulting from overshoot. The validity of the approach is confirmed by the simulation results. Further research work includes extending the proposed method to the fault-tolerant control problem of unknown nonlinear systems.