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Research Article

Self-repairing Control against Actuator Failures Using a Spiking Neuron Model

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ABSTRACT

This paper presents a new Self-repairing Control System (SRCS) for plants with actuator failures. The proposed SRCS uses the well-known Izhikevich spiking neuron model as a fault detector. When the actuator fails, the neuron model is excited and then spikes occur. Thus, counting up spikes makes it possible to find failures. Compared with the existing active fault-tolerant control systems, the SRCS has the following advantages: one can not only set a maximum detection time in advance, but also construct a simple control system whose structure is independent of the mathematical model of the plant. To confirm the effectiveness of the SRCS, this paper shows theoretical performance analysis and numerical simulation.

1. INTRODUCTION

In the previous works [1,2], several types of the Self-repairing Control Systems (SRCSs) have been developed as one of active Fault-tolerant Control Systems (FTCSs). The SRCS can automatically detect a failure and replace the failed component with the healthy backup so as to recover the stability of the control system. Compared with existing active FTCSs, the SRCS has the following advantages: (1) the maximum time of detection can be prescribed arbitrarily in advance, and (2) the structure of the control system does not depend on the mathematical model of the plant. Thus, early and robust FTC can be accomplished even if the plants have uncertainties.

Unfortunately, the conventional SRCSs have utilized an unstable detection filter [1] which is not suitable for the concept of the strong stability [3]. Recently, as a remedy, the well-known Izhikevich spiking neuron model [4] is used as a fault detector. A faulty signal in the control loop excites the neuron model. Hence, just counting up the number of spiking waves makes it possible to find failures. Because the boundedness of all the signals in the neuron model is always guaranteed, the requirement of the strong stability can be satisfied. Of course, the advantages of the original SRCSs are retained. Moreover, by utilizing the spiking neuron model, setting a threshold for fault detection is no longer needed. However, only an issue of sensor failure has been considered. A problem of actuator failure has not been solved.

In this paper, the SRCS using the spiking neuron model is modified to tolerate actuator failure. Furthermore, the theoretical analysis on stability and the mechanism for fault detection are shown. In addition, the effectiveness of the SRCS is confirmed through numerical simulation.

Throughout this paper, let $\mathbb{R}$, $\mathbb{R}^+$ and $\mathbb{N}$ denote the sets of real numbers, nonnegative real numbers and natural numbers including zero, respectively. In addition, with $x \in \mathbb{R}$, define the "sgn" function by

$$\mathrm{sgn}[x] = \begin{cases} 1 & (x \geq 0) \\ -1 & (x < 0) \end{cases}$$

2. PROBLEM STATEMENT

Consider a linear time invariant system of the form:

$$\Sigma_P : \dot{y} = ay + bu + \boldsymbol{h}^T \boldsymbol{z} \qquad \dot{\boldsymbol{z}} = \boldsymbol{F}\boldsymbol{z} + \boldsymbol{g}y \tag{1}$$

where, $y \in \mathbb{R}$ is the output, $u : \mathbb{R}^+ \to \mathbb{R}$ is the actual control input, $\boldsymbol{z} \in \mathbb{R}^{n-1}$ is the state, and $n \in \mathbb{N}$ is the order of the plant. Here, assume that the high frequency gain $b \in \mathbb{R}$ is positive. Moreover, $\boldsymbol{F} \in \mathbb{R}^{(n-1)\times(n-1)}$ is supposed to be a stable matrix (*i.e.*, all eigenvalues lie in the left half complex plane).

For occasion of failure, the two actuators are prepared. One is the primary actuator #1, and the other is the backup #2. Then, the actual control input can be expressed as follows.

$$u(t) = \begin{cases} u_1(t) & (t \leq t_D) \\ u_2(t) & (t > t_D) \end{cases} \tag{2}$$

where, $t_D \in \mathbb{R}^+$ is the detection time, and its detail will be discussed later. Each $u_i \in \mathbb{R}, i \in \{1, 2\}$ is the output of the actuator #*i*.

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Obviously, in healthy case, we have $u_i = u_c$, where $u_c : \mathbb{R}^+ \to \mathbb{R}$ is the designed control input. Based on dynamic redundancy (2), the primary actuator #1 is usually utilized, but it is switched to the backup when the failure is detected.

The failure scenario to be considered here, is expressed as follows:

$$u_1(t) = \varphi,\ t \geq t_F \tag{3}$$

where, $t_F \in \mathbb{R}^+$ is the unknown failure time, and $\varphi \in \mathbb{R}$ is the unknown stuck value. Such a failure occurs when the actuator gets stuck.

The problem is to design the SRCS, which can replace the failed actuator with the backup so as to maintain the stability and guarantee the convergence property of y:

$$\limsup_{t\to\infty} |y(t)| \leq \lambda \tag{4}$$

for arbitrarily given $\lambda \in \mathbb{R}^+$.

3. A CONTROL SYSTEM WITH A DETECTION FILTER

First of all, the detection filter is introduced based on the spiking neuron model [4,5]

$$\begin{aligned}\Sigma_D : \dot{v} &= \mathrm{sgn}[y](\theta_2 v^2 + \theta_0 - \eta w) + \theta_1 v + p(y + y^3)\\ \dot{w} &= \varepsilon(\gamma_1 \mathrm{sgn}[y]v + \gamma_0 - w)\end{aligned} \tag{5}$$

$$\text{if } \mathrm{sgn}[y]v \geq v_T \text{ then} \begin{cases} v \leftarrow \mathrm{sgn}[y]v_R \\ w \leftarrow w + w_R \end{cases} \tag{6}$$

where, $\theta_0 \in \mathbb{R}, \theta_1 \in \mathbb{R}, \theta_2 \in \mathbb{R}^+, \gamma_0 \in \mathbb{R}, \gamma_1 \in \mathbb{R}$ and $\eta \in \mathbb{R}^+$ are designed parameters, whose details will be discussed in the next section. Also, $v_T \in \mathbb{R}^+$ is the threshold for the "auxiliary resetting" (for spiking). To avoid degradation of stability by spikes, the resetting rule (6) should be invalid before the steady state.

Next, the high-gain feedback controller is designed by

$$\Sigma_C : u_c = -\frac{p^2}{b}(y + v + y^3 + v^3) \tag{7}$$

where, $p \in \mathbb{R}^+$ is the feedback gain to stabilize both the plant and the detection filter.

Then, the following lemma stands.

Lemma 1. *Consider the control system constructed by (1)–(7). But, the resetting rule (6) is supposed to be invalid. If there is no failure, then all of the signals in the control system are bounded. Furthermore, regarding convergence of the plant output, the inequality (4) holds.*

Proof. Suppose that there is no failure, *i.e.*, $u = u_c$. Now, define the new variable: $s : \mathbb{R}^+ \to \mathbb{R}$ by

$$s := y + v \tag{8}$$

From (1), (5), (7) and (8), it is shown that

$$\begin{aligned}\dot{s} = &-(p^2 - p - a)s - p^2 s^3 - (p - a)v - pv^3\\ &+ 3(p^2 - p)s^2 v - 3(p^2 - p)sv^2 + \boldsymbol{h}^T \boldsymbol{z}\\ &+ \mathrm{sgn}[y]\theta_2 v^2 + \theta_1 + \mathrm{sgn}[y]\theta_0 - \mathrm{sgn}[y]\eta w\end{aligned} \tag{9}$$

$$\dot{\boldsymbol{z}} = \boldsymbol{Fz} + \boldsymbol{g}s - \boldsymbol{g}v \tag{10}$$

$$\begin{aligned}\dot{v} = &-pv - pv^3 + \mathrm{sgn}[y]\theta_2 v^2 + \theta_1 v\\ &+ \mathrm{sgn}[y]\theta_0 - \mathrm{sgn}[y]\eta w\\ &+ ps + ps^3 - 3ps^2 v + 3psv^2\end{aligned} \tag{11}$$

Consider the positive definite function $V : \mathbb{R}^+ \to \mathbb{R}^+$ as,

$$V := \frac{1}{2}\left\{s^2 + \delta_1 \boldsymbol{z}^T \boldsymbol{Pz} + v^2 + \delta_2 w^2\right\} \tag{12}$$

where, $\boldsymbol{P} \in \mathbb{R}^{(n-1)\times(n-1)}$ is the positive definite matrix which satisfies $\boldsymbol{F}^T \boldsymbol{P} + \boldsymbol{P}^T \boldsymbol{F} = -2\boldsymbol{Q}$ for any positive definite $\boldsymbol{Q} \in \mathbb{R}^{(n-1)\times(n-1)}$. Also, $\delta_1 \in \mathbb{R}^+$ and $\delta_2 \in \mathbb{R}^+$ are small positive constants. Taking the time derivative of V gives

$$\begin{aligned}\dot{V} = &-(p^2 - p - a)s^2 - p^2 s^4 - (p - a)sv - psv^3\\ &+ 3(p^2 - p)s^3 v - 3(p^2 - p)s^2 v^2 + \boldsymbol{h}^T \boldsymbol{z}s\\ &+ \mathrm{sgn}[y]\theta_2 sv^2 + \theta_1 s + \mathrm{sgn}[y]\theta_0 s - \mathrm{sgn}[y]\eta ws\\ &- \delta_1 \boldsymbol{z}^T \boldsymbol{Qz} + \delta_1 \boldsymbol{z}^T \boldsymbol{Pg}s + \delta_1 \boldsymbol{z}^T \boldsymbol{Pg}v\\ &- pv^2 - pv^4 + \mathrm{sgn}[y]\theta_2 v^3 + \theta_1 v^2\\ &+ \mathrm{sgn}[y]\theta_0 v - \mathrm{sgn}[y]\eta wv\\ &+ psv + ps^3 v - 3ps^2 v^2 + 3psv^3\\ &+ \delta_2 \varepsilon \gamma_1 \mathrm{sgn}[y]vw + \delta_2 \varepsilon \gamma_0 w - \delta_2 \varepsilon w^2\end{aligned} \tag{13}$$

Assume that p is chosen so that

$$p^2 - p - a > 0 \tag{14}$$

Then, the time derivative of V can be evaluated as

$$\begin{aligned}\dot{V} \leq &-\alpha_1 s^2 - \alpha_2 s^4 - \delta_1 \alpha_3 \|z\|^2 - \alpha_4 v^2 - \alpha_5 v^4\\ &- \frac{1}{2}\delta_2 \varepsilon w^2 + 2\delta_2 \varepsilon \gamma_0^2 + \delta_3\end{aligned} \tag{15}$$

where, $\delta_3 \in \mathbb{R}^+$ is a small positive constant, and

$$\begin{aligned}\alpha_1 &= p^2 - p - a - \frac{|a|}{2} - \frac{3}{4\delta_1}\|\boldsymbol{h}\|^2 - \frac{3\theta_1^2}{4\delta_3} - \frac{3\theta_0^2}{4\delta_3} - \frac{2\eta^2}{\delta_2 \varepsilon} - \frac{3}{4\delta_1}\|\boldsymbol{Pg}\|^2\\ \alpha_2 &= \frac{1}{4}p^2 - p - \frac{|\theta_2|}{4}\\ \alpha_3 &= \lambda_{\min}[\boldsymbol{Q}] - 1\\ \alpha_4 &= p - \frac{|a|}{2} + \frac{3}{4\delta_1}\|\boldsymbol{Pg}\|^2 - |\theta_2| - |\theta_1| - \frac{3\theta_0^2}{4\delta_3} - \frac{2\eta^2}{\delta_2 \varepsilon} - 2\delta_2 \varepsilon \gamma_1^2\\ \alpha_5 &= \frac{1}{4}p - |\theta_2|\end{aligned}$$

Choose sufficiently large p. Then, $\alpha_i > 0 \forall i$. Hence, from (15), it follows that

$$\dot{V}(t) \leq -\alpha V(t) + \beta,\ t \in [0, t_F) \tag{16}$$

where

$$\begin{aligned}\alpha &= \min\left\{2\alpha_1, \frac{2\alpha_2}{\lambda_{\max}[\boldsymbol{P}]}, 2\alpha_3, \varepsilon\right\}\\ \beta &= 2\delta_2 \varepsilon \gamma_0^2 + \delta_3\end{aligned} \tag{17}$$

Solving the differential inequality (16), the following inequality can be obtained.

$$V(t) \le V(0)e^{-\alpha t} + \frac{\beta}{\alpha},\ t \in [0,\ t_F) \tag{18}$$

Therefore, if no failure occurs, that is, $t_F = \infty$, then all the signals in the control system are bounded. Moreover, taking $|y| \le |s| + |v|$ into consideration, it follows that

$$\limsup_{t\to\infty} |y(t)| \le \limsup_{t\to\infty} 2\sqrt{V(t)} \le 2\sqrt{\frac{2\beta}{\alpha}} \tag{19}$$

It is clear that $2\sqrt{2\beta/\alpha} < \lambda$ for sufficiently small δ_2 and δ_3. This means that the inequality (4) holds if no failure occurs. The proof is completed.

Regarding the filtered signal v, from (18), it follows that

$$\limsup_{t\to\infty} |v(t)| \le \lambda \tag{20}$$

Enable the resetting rule (6) with the threshold v_T greater than λ, in the steady state. Then, as long as the actuator is healthy, no spike occurs and so the stability and convergence property (4) can be ensured.

4. ACTUATOR FAILURE DETECTION

In this section, the real-time failure detection is shown using the detection filter constructed by (5) and (6).

For preparation, refer to the Izhikevich neuron model [4] of the same scale and parameters as (5):

$$\begin{aligned} \dot{v} &= \theta_2 v^2 + \theta_1 v + \theta_0 - \eta w \\ \dot{w} &= \varepsilon(\gamma_1 v + \gamma_0 - w) \end{aligned} \tag{21}$$

where, θ_0, θ_1, θ_2, γ_0, γ_1 and η are supposed to be chosen such that the bursting appears as shown in Figure 1.

In the figure, $t_B \in \mathbb{R}^+$ represents the bursting time, and it can be arbitrarily shortened by setting the parameters. Furthermore, $n_R \in \mathbb{N}$ is the number of spikes in the pattern, and it also can be prescribed by parameters. The figure shows an example of $\eta_R = 5$.

Now, consider the case when the actuator gets stuck. Assume that t_B is set so small that there exists a finite time $t_E \ge t_F$ defined by

$$t_E = \inf\{T \ge t_F \mid \mathrm{sgn}[y(s)] = \mathrm{sgn}[y(T)],\ T \le s < T + t_B\} \tag{22}$$

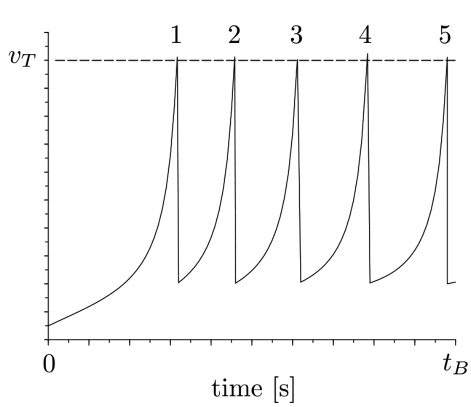

Figure 1 | The bursting pattern of the spiking neuron model.

Because of continuity of y and boundedness of $\dot{y}$ on a finite time interval, the sign of y does not change in a neighborhood of the failure time t_F. This implies that $t_E = t_F$ for sufficiently small t_B.

In the case of sgn $[y(t_E)] = 1$, from (5), the behaviors of the signals in the detection filter obey

$$\begin{aligned} \dot{v} &= \theta_2 v^2 + \theta_1 v + \theta_0 - \eta w + p(y + y^3) \\ \dot{w} &= \varepsilon(\gamma_1 v + \gamma_0 - w) \end{aligned} \tag{23}$$

In the above equations, the effect of the control input u_c gets lost because the actuator fails. Hence, the bursting occurs in the signal v.

By comparing (21) with (23), it is regarded that the term $p(y + y^3) > 0$ is additionally injected to the spiking model (21). Generally, a larger stimulus causes more spikes. Therefore, the bursting becomes more frequently than the pattern of (21) on the time period $[t_E, t_E + t_B)$.

In the case of sgn $[y(t_E)] = -1$, the negative spikes of the same bursting pattern as above is induced.

Next, consider the case when there is no failure. Then the spiking of detection filter does not occur because the filtered signal v is suppressed smaller than v_T.

Consequently, from the above discussion, the bursting pattern appears only when the actuator fails. Thus, by just counting the number of the spikes, the failure can be found. Specifically, the detection time t_D is defined by

$$t_D := \min\{t \mid c_R(t) \ge n_R\} \tag{24}$$

where, $c_R \in \mathbb{N}$ is the counted number of the spikes in the filtered signal v.

From (24), it follows that $t_D \le t_E + t_B$. Hence, by setting t_B small, the maximum detection time can be shortened arbitrarily.

After replacing the failed actuator, the boundedness of all the signals in the control system are guaranteed again, and the plant output can converge to the small region, that is, the inequality (4) holds.

The overall control system is illustrated in Figure 2.

Remark. If there does not exist finite t_E, that is, $t_E = \infty$, then the failure may not be found theoretically. As a remedy, it is recommended

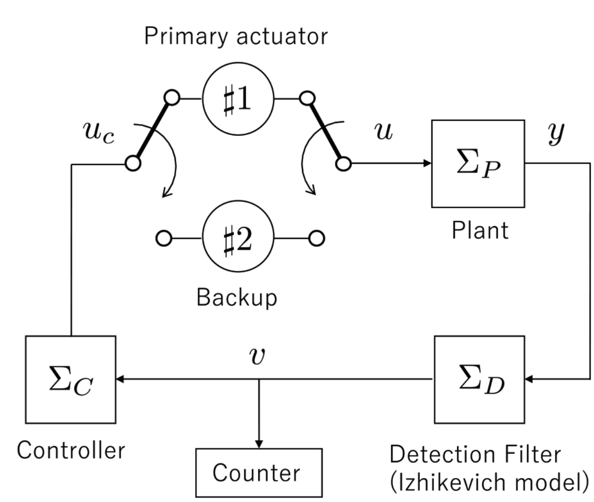

Figure 2 | Block diagram of the SRCS against actuator failures.

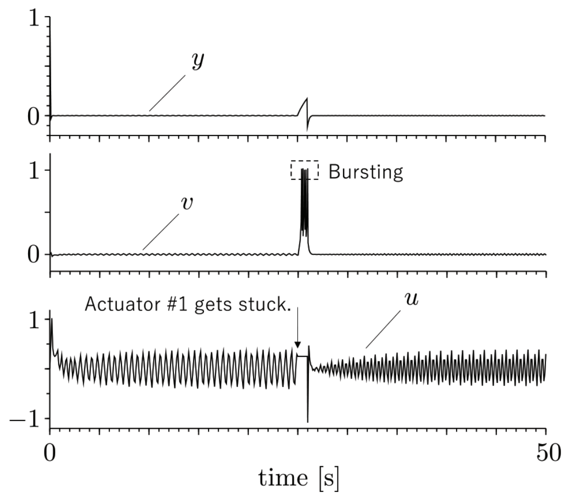

Figure 3 Simulation results: the plant output (top), the filtered signal (middle) and the actual input (bottom).

to monitor the plant output y for checking the convergence property. As long as the inequality (4) holds, the control objective can be achieved regardless of presence of failures.

5. NUMERICAL EXAMPLES

To confirm the effectiveness of the proposed method, the numerical simulation is explored.

Consider the following unstable plant.

$$\begin{aligned} \dot{y} &= -y + u + z, \ y(0) = 1 \\ \dot{z} &= -2z + y, \ z(0) = -1 \end{aligned} \tag{24}$$

The failure scenario is supposed that

$$t_F = 25[s], \ \varphi = u(t_F) \tag{25}$$

For the above plant, the parameters for the detection filter are selected as $\theta_0 = -0.06$, $\theta_1 = -0.6$, $\theta_2 = 4$, $\gamma = \delta = 1$, $\varepsilon = 0.02$, $\gamma_0 = -6$, $\gamma_1 = 20$. Also, the parameters for resetting are $v_T = 1$, $v_R = 0.2$, $w_R = 2$. The prespecified number of the spikes in the bursting pattern is supposed to be five per second, that is, $n_R = 5$ within almost $t_B = 1$ [s]. At last, the controller gain is chosen as $p = 6$.

The simulation results are shown in Figure 3 where the plant output y (top), the filtered signal v (middle), and the actual input u (bottom) are shown.

From the simulation results, the failed actuator can be replaced at the detection time $t_D \cong 26$ [s]. Also, the plant output y converges to a very small ball before and after the failure.

6. CONCLUSION

This paper has presented the new SRCS that can find actuator failure by using the Izhikevich neuron model. From theoretical and numerical analysis, it is shown that fault-tolerant control can be accomplished.

In the previous work [5], the basic idea of the SRCS using the spiking neuron model has already been proposed for plants with sensor failures. The main differences from the previous version are as follows: the actuator failures can be tolerated, and in constructing the detection filter, the time derivative of the plant output y is not utilized. Thus, the control system not only becomes simple but also has more robustness with respect to component failures and noises in the plant output.

CONFLICTS OF INTEREST

The author declares no conflicts of interest.

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REFERENCES

[1] M. Takahashi, Self-repairing control against unknown sensor failures and biases, Asian J. Control 15 (2013), 1215–1223.

[2] M. Takahashi, Self-repairing PI/PID control against sensor failures, Int. J. Innov. Comput. Inform. Control 12 (2016), 193–202.

[3] A. Yanou, M. Minami, T. Matsuno, Strong stability rate for control systems using coprime factorization, Trans. Soc. Instrum. Control Eng. 50 (2014), 441–443 (in Japanese).

[4] E.M. Izhikevich, Simple model of spiking neurons, IEEE Trans. Neural Netw. 14 (2003), 1569–1572.

[5] M. Takahashi, Izhikevich model-based self-repairing control for plants with sensor failures and disturbances, J. Robot. Network. Artif. Life 6 (2019), 105–108.

AUTHOR INTRODUCTION

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