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ADAPTIVE NEURAL EVENT-TRIGGERED DESIGN FOR THE MOLTEN STEEL LEVEL IN A STRIP CASTING PROCESS

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This paper considers an adaptive neural event-triggered control problem of the molten steel level for twin roll strip casting systems with the inclined angle. Firstly, the model is improved and simplified into an affine nonlinear system by exploiting input compensation technique. Then, an adaptive observer is established based on radial basis function neural network (RBFNN). Furthermore, an adaptive event-triggered control scheme and corresponding adaptive updated laws are designed. It is proved that the proposed control method can guarantee the system output can follow reference signal and all closed-loop signals are bounded. Finally, the validity of the control scheme is verified through semi-experimental system dynamic model.

Keywords: casting process, strip, mathematic model, molten steel level control, radial basis function neural network (RBFNN)

INTRODUCTION

In recent years, with the development of machinery manufacturing industry, the produce technologies of thin strip steel have attracted wide attention, and produced a lot of research results [1-2]. Combining continuous casting and hot rolling, twin-roll casting and rolling has the advantages of reducing cost, saving energy, saving space and so on, and can significantly improve the microstructure and properties of metals [3-4]. Compared with the horizontal two-roll casting, the two-roll inclined casting can reduce the specific gravity segregation and increase the casting speed [5].

In practice, the model of double roll strip steel inclined continuous casting system is strongly nonlinear and coupled, thus the controller design is very difficult. In references [6] and [7], two adaptive fuzzy controller design problems were studied for twin-roll strip casting system, and the way that was they use the mean value theorem to transform the non-affine system to an affine system, then by using the universal approximation capability of fuzzy logic systems, a novel adaptive tracking controller was deigned to ensure the tracking error convergence. In [8], an adaptive tracking control method was considered with event triggering input. In [9], a neural network adaptive control for interconnected nonlinear system. Inspired by [6] and [9], in this paper, an event-triggered adaptive control is studied for a twin roll strip casting system with an inclined angle. Firstly, the twin roll strip casting system is degenerated into an affine system. Then, adaptive neural observer and event triggering controller are designed to achieve the control goal. Finally, it is shown that the output signal of the molten steel level can track the reference signal through semi-experimental system dynamic model.

SYSTEM MATHMATICAL MODEL OF THE STRIP CASTING PROCESS

Molten metal level equation

Similar to the reference [6], the equation of liquid steel level in strip continuous casting process is:

$$\frac{dV}{dt} = L_r \left[y\frac{dx_g}{dt} + \left(x_g + 2R - 2\sqrt{R^2 - y^2} \right) \frac{dy}{dt} \right] \tag{1}$$

where $x_g(t)$ is the roll gap, R is the roll radius, $y(t)$ is the height of molten metal, and L_r is the length of the roll cylinders. V is the volume of the molten steel stored between the twin-roll cylinders with $\frac{dV}{dt} = Q_{in} - Q_{out} = \tau u - L_r x_g v$, u is the electric servomotor control input, τ is a corresponding control gain, v is the roll surface tangential velocity.

However, in the process of double roll inclined casting and rolling, the shape of molten pool changes, resulting in the increase of inclined angle, so it is of great significance to consider the angle β. The double-roll inclined casting and rolling system with inclined angle is shown in Figure 1.

In addition, ω is the direction. Consider that there is a linear relationship between the height of molten metal y and the roll gap x_g, we can assume that $x_g = ky$, it is easy to get $\frac{dx_g}{dt} = k\frac{dy}{dt}$, substitute it into (1) and consider the inclined angle problem, we can get the following form:

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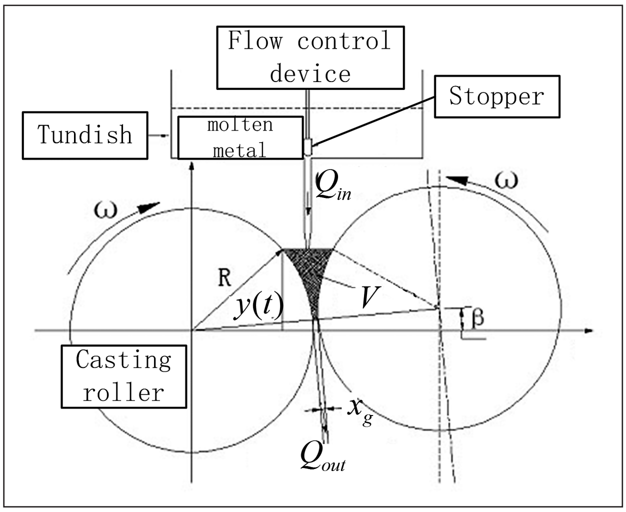

Figure 1 Schematic view of the twin-roll inclined casting with an inclined angle

$$\frac{d^2y}{dt^2}=g(y,\dot{y},\ddot{y},\beta)u-\frac{dy}{dt}f_1(y,\beta)-f_2(y,\beta) \qquad (2)$$

where $g(\cdot)=\frac{\tau}{L_r N}y$, $f_1(\cdot)=\frac{ky^2\upsilon}{N}$, $f_2(\cdot)=\frac{N_0}{N}$, $N = y\cos\beta - (2R + ky)\cos\beta\sin\beta$, $N_0 = (2R + ky)\cos\beta - \sqrt{R^2-(y-(2R+ky)\sin\beta)^2} - \sqrt{R^2-y^2}$. Next, we introduce the following coordinate transformations $x_1 = y$, $x_2=\frac{dy}{dt}$, $F(y,\dot{y},\ddot{y},\beta,u)=\tau_0 u+\frac{dy}{dt}f_1+f_2+(g-\tau_0)u$, consider the external disturbance $\omega_i(t)$, so the continuity equation of molten steel (2) can be described by following differential equations:

$$\begin{aligned}\dot{x}_1&=x_2+\omega_1\\ \dot{x}_2&=\tau_0u+F(y,\dot{y},\ddot{y},\beta,u)+\omega_2\\ y&=x_1\end{aligned} \qquad (3)$$

In this paper, we assume that the state x_2 is unavailable. Accordingly, our objective is to design an adaptive neural event trigger controller u such that the system output y can track reference signal y_r in the case of disturbances and all closed loop signals are bounded. To achieve the tracking objectives, we need to introduce the following assumption.

Assumption 1 [7] For the nonlinear system (3), the reference signals y_r and its first time derivative $\dot{y}_r$ are assumed known and bounded function; besides, there are unknown constants ω_i satisfying $|\omega_i|\le\bar{\omega}_i$, $i = 1,2$.

Lemma 1 Similar to [9], the RBFNN has great ability to approximate an unknown function. For a compact set Ω_x, $\forall\varepsilon > 0$, one has

$$f(x)=\vartheta^T\varphi+\varsigma(x),\ \ |\varsigma(x)|<\varepsilon \qquad (4)$$

where $x \in \Omega_x$, $\zeta(x)$ is approximate error, $\vartheta = [\vartheta_1, ..., \vartheta_N]^T$ represents weight vector, $\varphi = [\varphi_1, ..., \varphi_N]^T$ is the basis function vector, and ideal weight vector will be chosen as

$$\vartheta^*=\arg\min_{\vartheta\in\Omega_\vartheta}\{\sup_{x\in\Omega_x}|f(x)-\vartheta^T\varphi|\} \qquad (5)$$

ADAPTIVE NEURAL EVENT- TRIGGERED CONTROL DESIGN AND STABILITY ANALYSIS

Adaptive event-triggered control design

According to Lemma 1, the nonlinear function $F(y, \dot{y}, \ddot{y}, \beta, u)$ can be approximated as $F = \vartheta^T\varphi + \zeta$. Then design an adaptive neural observer to estimate the unmeasured state as

$$\begin{aligned}\dot{\hat{x}}_1&=x_2+l_1(\hat{y}-\hat{y})\\ \dot{\hat{x}}_2&=\tau_0u+l_2(y-\hat{y})+\hat{\vartheta}^T\varphi\\ \hat{y}&=\hat{x}_1\end{aligned} \qquad (6)$$

Denote $e_i = x_i-\hat{x}_i, i=1,2$, $e = [e_1, e_2]^T$ and $\tilde{\vartheta}$ is error vector with $\tilde{\vartheta} = \vartheta - \hat{\vartheta}$. According to (3) and (6), the error systems can be written as:

$$\dot{e}=Ae+B\left(\tilde{\vartheta}^T\varphi+\varsigma\right)+\omega \qquad (7)$$

where $A=\begin{bmatrix}-l_1 & 1\\ -l_2 & 0\end{bmatrix}, B=\begin{bmatrix}0\\1\end{bmatrix}, \omega=\begin{bmatrix}\omega_1\\ \omega_2\end{bmatrix}$, for any matrix $Q = Q^T > 0$, we can design the parameters l_1 and l_2 to make $A^TP + PA = -Q$ and $P = PT > 0$. Therefore, the following systems can be applied for the iterative design

$$\begin{aligned}\dot{e}&=Ae+B\left(\tilde{\vartheta}^T\varphi+\varsigma\right)+\omega\\ \dot{x}_1&=x_2+\omega_1\\ \dot{\hat{x}}_2&=\tau_0u+l_2e_1+\hat{\vartheta}^T\varphi\end{aligned} \qquad (8)$$

For desired trajectory y_r, defining error variables $z_1 = x_1 - y_r$, $z_2 = \hat{x}_2 - \alpha$, α is virtual controller in the design process. Selecting the following Lyapunov function V_1 as:

$$V_1=e^TPe+\frac{1}{2}z_1^2 \qquad (9)$$

By taking the time derivative of V_1, it leads to

$$\begin{aligned}\dot{V}_1=&-e^TQe+2e^TPB\left(\tilde{\vartheta}^T\varphi+\varsigma\right)+2e^TP\omega\\ &+z_1(z_2+\alpha+\omega_1-\dot{y}_r)\end{aligned} \qquad (10)$$

Utilizing Young's inequality we can get

$$\begin{aligned}&2e^TPB\left(\tilde{\vartheta}^T\varphi+\varsigma\right)+2e^TP\omega\\ &\le3\|e\|^2+\|P\|^2\tilde{\vartheta}^T\tilde{\vartheta}+\|P\|^2\varepsilon^2+\|P\bar{\omega}\|^2\\ &z_1\omega_1\le\frac{1}{2}z_1^2+\frac{1}{2}\bar{\omega}_1^2\end{aligned} \qquad (11)$$

where $\varphi^T\varphi \le 1$, choose virtual control as

$$\alpha=-c_1z_1-\frac{1}{2}z_1+\dot{y}_r \qquad (12)$$

where $c_1 > 0$ is a design parameter, then substituting (12), (13) into (11) yields

$$\begin{aligned}\dot{V}_1\le&-(\lambda_{\min}(Q)-3)\|e\|^2+\|P\|^2\tilde{\vartheta}^T\tilde{\vartheta}\\ &-c_1z_1^2+z_1z_2+\beta_1\end{aligned} \qquad (13)$$

where $\beta_1=\frac{1}{2}\bar{\omega}_1^2+\|P\bar{\omega}\|^2+\|P\|^2\varepsilon^2$. Next we choose the Lyapunov function V_2 as:

$$V_2=V_1+\frac{1}{2}z_2^2+\frac{1}{2}\tilde{\vartheta}^T\Gamma^{-1}\tilde{\vartheta}+\frac{1}{2r}\tilde{\Theta}^2 \qquad (14)$$

where $\Gamma > 0$, $r > 0$ are design parameters, $\tilde\Theta$ is estimation error with $\tilde\Theta = \Theta - \hat\Theta$ and Θ is defined as $\Theta = \|\psi\|^2$. So the derivative of V_2 is

$$\begin{aligned}\dot V_2 &= \dot V_1 + z_2(\tau_0 u + l_2 e_1 + \hat\vartheta^T\varphi)\\ &\quad - r^{-1}\tilde\Theta\dot{\hat\Theta} - \tilde\vartheta^T\Gamma^{-1}\dot{\hat\vartheta}\end{aligned} \tag{15}$$

Then, the following triggering algorithm for the control input can be designed as

$$\begin{aligned}&u(t) = h(t_k), \forall t \in [t_k, t_{k+1})\\ &t_{k+1} = \inf\{t \in R \mid |\zeta(t)| \ge M\}, t_1 = 0\end{aligned} \tag{16}$$

where $\zeta(t) = h(t) - u(t)$ is the error, $M > 0$ is a design parameter, $h(t)$ is controller in (20), t_k, $k \in Z^+$ is update time. Particularly, control input will keep as constant $h(t_k)$ in $[t_k, t_{k+1}]$. By (16), it is easy to get $u(t) = h(t) - \delta(t) M$, with $\delta(t)$ satisfying $\delta_0(t_k) = 0$, $\delta_0(t_{k+1}) = 1$ and $|\delta_0(t_k)| \le 1$. So (15) can be rewritten as

$$\begin{aligned}\dot V_2 &\le \dot V_1 - r^{-1}\tilde\Theta\dot{\hat\Theta} - \tilde\vartheta^T\Gamma^{-1}\dot{\hat\vartheta}\\ &\quad + z_2(\tau_0 h(t) - \tau_0\delta(t)M + l_2 e_1 + \hat\vartheta^T\varphi)\end{aligned} \tag{17}$$

Define the nonlinear compound function as $\bar F = \vartheta^T\varphi - \varsigma + l_2 e_1 + z_2 - \tau_0\delta(t)M = \psi_1^T\xi + \iota_1$, with $|\iota_1| \le \bar\iota_1$, so we can get

$$z_2\bar F \le \frac{1}{2a^2}z_2^2\Theta\xi^T\xi + \frac{1}{2}a^2 + \frac{1}{2}z_2^2 + \frac{1}{2}\bar\iota_1^2 \tag{18}$$

where the constant a is positive. Combining (13), (17) and (18), we can get

$$\begin{aligned}\dot V_2 &\le -(\lambda_{\min}(Q) - 3)\|e\|^2 + \|P\|^2\tilde\vartheta^T\tilde\vartheta - c_1z_1^2 + \beta_1\\ &\quad + \frac{1}{2}a^2 + \frac{1}{2}\bar\iota_1^2 + z_2(\tau_0 h + \frac{1}{2}z_2 + \frac{1}{2a^2}z_2\hat\Theta\xi^T\xi)\\ &\quad - \tilde\vartheta^T\Gamma^{-1}(\dot{\hat\vartheta} + \Gamma z_2\varphi) - r^{-1}\tilde\Theta(\dot{\hat\Theta} - \frac{r}{2a^2}z_2^2\xi^T\xi)\end{aligned} \tag{19}$$

Further, design the continuous controller and adaptive updated laws as

$$h(t) = \frac{1}{\tau_0}(-c_2z_2 - \frac{1}{2}z_2 - \frac{1}{2a^2}z_2\hat\Theta\xi^T\xi) \tag{20}$$

$$\begin{aligned}\dot{\hat\vartheta} &= -\Gamma\sigma\hat\vartheta - \Gamma z_2\varphi\\ \dot{\hat\Theta} &= -\varrho\hat\Theta + \frac{r}{2a^2}z_2\xi^T\xi\end{aligned} \tag{21}$$

Thus the following inequation can be get

$$\begin{aligned}\dot V_2 &\le -(\lambda_{\min}(Q) - 3)\|e\|^2 + \|P\|^2\tilde\vartheta^T\tilde\vartheta - c_1z_1^2 -\\ &\quad c_2z_2^2 + \beta_1 + \frac{1}{2}a^2 + \frac{1}{2}\bar\iota_1^2 + \sigma\tilde\vartheta^T\hat\vartheta + \frac{\varrho}{r}\tilde\Theta\hat\Theta\end{aligned} \tag{22}$$

Stability analysis

Theorem 1 Consider the molten steel leveling dynamics system (3) satisfying Assumption 1. The designed controller (20) and adaptive updated laws (21) can guarantee that system output y can follow reference signal y_r and all closed-loop signals are bounded. In addition, the Zeno behavior can be effectively avoid.

Proof: Note that $\tilde\vartheta^T\hat\vartheta \le -0{,}5\|\tilde\vartheta\|^2 + 0{,}5\|\vartheta\|^2$ and $\tilde\Theta\hat\Theta \le -0{,}5\tilde\Theta^2 + 0{,}5\Theta^2$, we can select the parameter σ so that $\sigma - \|P\|^2/2 = \gamma > 0$, thus (22) becomes

$$\begin{aligned}\dot V_2 &\le -(\lambda_{\min}(Q) - 3)\|e\|^2 - 0.5\lambda\|\tilde\vartheta\|^2\\ &\quad - c_1z_1^2 - c_2z_2^2 - \frac{\varrho}{2r}\tilde\Theta^2 + \beta_2\\ &\le -a_0V_2 + \beta_2\end{aligned} \tag{23}$$

with $a_0 = \min\{\frac{\lambda_{\min}(Q) - 3}{\lambda_{\max}(P)}, 2c_1, 2c_2, \frac{\lambda}{\lambda_{\max}(\Gamma)}, \varrho\}$ $\beta_2 = \beta_1 + \frac{1}{2}(a^2 + \bar\iota_1^2 + \|\vartheta\|^2 + \Theta^2)$. Multiply both sides by $e^{a_0 t}$, integrating (23) from 0 to t gives $0 \le V_2 \le V_2(0) + a_0/\beta_2$, this means the output can follow reference signal and all signals are bounded. Besides, for $\forall t \in [t_k, t_{k+1})$, one has $d|\zeta|/dt = sign(\zeta)\dot\zeta \le |\dot h|$, obviously, there must exist a constant π such that the lower bound of inter-execution intervals t^* satisfies $t^* \ge \frac{M}{\pi}$, thus Zeno behavior [8] is effectively avoided. This completes the proof.

SIMULATION STUDIES

Consider the molten metal level equation (2), the corresponding parameters are selected as R = 150 mm, L_r = 200 mm, v = 10 mpm and β = 3°, the desired roll gap is 3 mm, the initial molten steel level is 70 mm, and the reference signal is sin(t), respectively. According to (5), the number of the NNs nodes is N = 5 from -2 to 2, width of the Gaussian functions is 0,5.

The control parameters are selected as c_1 = 400, c_2 = 60, l_1 = 5, l_2 = 50, $\Gamma = \sigma = \varrho$ =10, τ_0 = 90, r = 1, M = 0,8. The initial values are selected as $x(0) = [0{,}1\ \ 0{,}1]^T$, $\hat x(0) = [0{,}1\ \ 0{,}1]^T$, $\hat\vartheta_i(0) = 1$, $i = 1, \cdots 5$, $\hat\Theta(0) = 0{,}8$. The simulation results are shown in Figures 2-4. From Figure 2, it can be seen that the system output y can track reference signals y_r, and track error z_1 can converge to the compact set of the origin. The boundedness of updated laws $\hat\vartheta$ and $\hat\Theta$ are revealed in Figure 3. Figure 4 shows the continuous control input and trigger control input are all bounded, as well as gives the time interval of triggering event.

CONCLUSIONS

In this paper, an adaptive neural event-triggered control problem is considered for twin roll strip casting process with the inclined angle. It is worth note out that the improved mathematical model is effectively decoupled using input compensation method. Based on RBFNN, we design an adaptive neural observer to estimate the unknown states of the system and construct an adaptive event triggering controller to achieve the control purpose. It is proved by stability analysis that all the closed-loop signals are bounded and the tracking error of the molten steel level can converge to a compact set

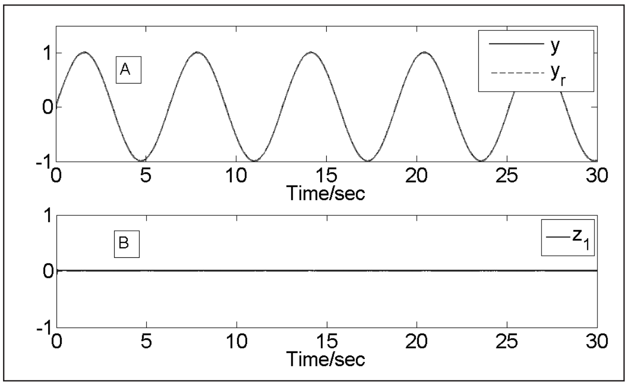

Figure 2 A: trajectories of y and y_r; B: trajectory of the tracking error z_1.

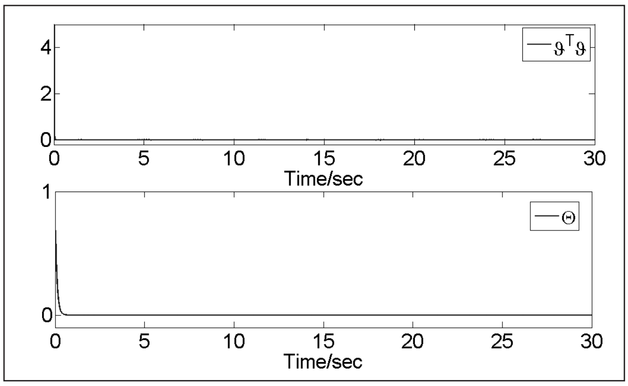

Figure 3 Trajectories of $\hat{\vartheta}$ and $\hat{\Theta}$.

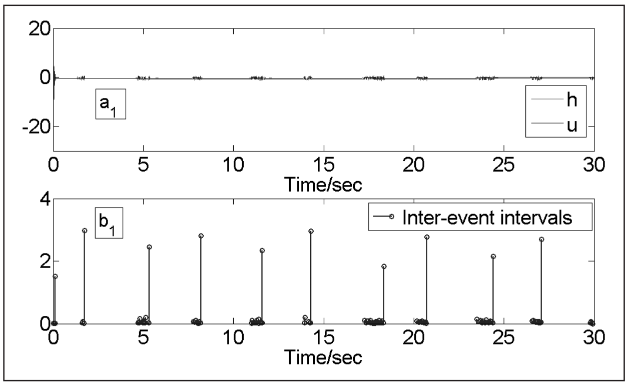

Figure 4 a_1: trajectories of h and u; b_1: time intervals of triggering event.

at the origin. Moreover, the designed controller can avoid the Zeno behavior. Besides, simulation results show the effectiveness of the proposed adaptive event triggered control method.

Acknowledgments

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Note: The responsible translators for English language is J. Wang-University of Science and Technology Liaoning, China