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Exponential Passivity Criteria for BAM Neural Networks with Time-Varying Delays

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Abstract—In this paper,the exponential passivity criteria for BAM neural networks with time-varying delays is studied.By constructing new Lyapunov-Krasovskii functional and dividing the delay interval into multiple segments,a novel sufficient condition is established to guarantee the exponential stability of the considered system.Finally,a numerical example is provided to illustrate the usefulness of the proposed main results.

Keywords—BAM neural networks, Exponential passivity, LMI approach, Time-varying delays.

I. Introduction

BI-DIRECTIONAL associative memory (BAM) neural networks have been extensively studied in recent years due to its wide application in various areas such as image processing,automatic control,pattern recognition,and so on. Therefore,it is meaningful and important to study the BAM neural network.They were originally introduced by Kosko [1-3],have attracted by many researchers.The problems of robust passivity,delay-dependent and stability have been well investigated;see,for example,[7,8,10-24] and references cited therein.Moreover,the problems of dissipativity of neural networks were proposed in [4,9].

Recently,the exponential passivity of neural networks with time-varying delays has been studied.A typical example of it is [5],where sufficient conditions have been obtained for considered neural networks to be exponential passivity.But in [5,6],the information of neuron activation functions and the involved time-varying delays has not been adequately considered,which may lead to some conservatism.In [7], the derivative of a time-varying delay be less than 1,but it is not necessary to consider the derivative of a time-varying delay less than 1.

As so far,the problems of exponential passivity of BAM neural networks with time-varying delays has not been widely studied,which motivates this work.in the present paper,we investigate the problem of delay-dependent exponential passivity for BAM neural networks with time-varying delays.The delay belongs to a given interval,and the restriction that the derivative of a time-varying delay be less than 1 is removed. A novel sufficient condition is established by dividing the delay interval into multiple segments,and constructing new Lyapunov-Krasovskii functional which contains some new integral terms.Finally, in order to show the feasibility of the proposed criteria in this paper,a numerical example is considered.

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II. Problem Statement

Consider the following BAM neural networks with time varying delays described by

$$\begin{cases} \dot{x}(t) = -Ax(t) + Cf(y(t)) + Ef(y(t-h(t))) + \mu(t) \\ z_1(t) = f(y(t)) + f(y(t-h(t))) + \mu(t) \\ \dot{y}(t) = -By(t) + Dg(x(t)) + Fg(x(t-\varsigma(t))) + \nu(t) \\ z_2(t) = g(x(t)) + g(x(t-\varsigma(t))) + \nu(t) \end{cases} \tag{1}$$

where $x(t) = [x_1(t), x_2(t), \ldots, x_n(t)]^T \in R^n$ and $y(t) = [y_1(t), y_2(t), \ldots, y_n(t)]^T \in R^n$ denote the neuron state vectors;$g(x(t)) = [g_1(x_1(t)), g_2(x_2(t)), \ldots, g_n(x_n(t))]^T \in R^n$ and $f(y(t)) = [f_1(y_1(t)), f_2(y_2(t)), \ldots, f_n(y_n(t))]^T \in R^n$ are the neuron activation function;$A = diag\{a_i\} \in R^n$ and $B = diag\{b_i\} \in R^n$ are positive diagonal matrices;C and D are the connection weight matrices,E and F are the delayed connection weight matrices;$\mu(t)$ and $\nu(t)$ are the external input vector to neurons;$z_1(t)$ and $z_2(t)$ are the output vector of neuron networks.

The following assumptions are adopted throughout the paper.

Assumption 1: The delay $h(t)$ and $\varsigma(t)$ are time-varying continuous functions and satisfies:

$$0 \le \varsigma(t) \le \varsigma, \dot{\varsigma}(t) \le \varsigma_D, 0 \le h(t) \le h, \dot{h}(t) \le h_D \tag{2}$$

where $\varsigma, h, \varsigma_D$ and h_D are constants.

Assumption 2: Neuron activation function $g_i(\cdot), f_i(\cdot)$ in (1) satisfies the following condition:

$$\begin{aligned} &\delta_i^- \le \frac{f_i(\alpha) - f_i(\beta)}{\alpha - \beta} \le \delta_i^+ \\ &\sigma_i^- \le \frac{g_i(\alpha) - g_i(\beta)}{\alpha - \beta} \le \sigma_i^+ \\ &g_i(0) = 0, f_i(0) = 0, \alpha, \beta \in R, \alpha \ne \beta, i = 1, 2, \ldots, n. \end{aligned} \tag{3}$$

where
$\Sigma^+ = diag\{\delta_1^+, \delta_2^+, \ldots, \delta_n^+\}, \Sigma_- = diag\{\delta_1^-, \delta_2^-, \ldots, \delta_n^-\}$, $\Gamma^+ = diag\{\sigma_1^+, \sigma_2^+, \ldots, \sigma_n^+\}, \Gamma_- = diag\{\sigma_1^-, \sigma_2^-, \ldots, \sigma_n^-\}$

Thus,under this assumption,the following inequalities hold for any diagonal matrices $R_1, R_2 > 0$

$$y^T(t)\Sigma R_1 \Sigma y(t) - f^T(y(t))R_1 f(y(t)) \geq 0$$
$$x^T(t)\Gamma R_2 \Gamma x(t) - g^T(x(t))R_2 g(x(t)) \geq 0 \quad (4)$$

where

$$\Sigma = diag\{\delta_1, \delta_2, \ldots, \delta_n\}, \delta_i = \max_{1\leq i\leq n}\{|\delta_i^+|, |\delta_i^-|\},$$
$$\Gamma = diag\{\sigma_1, \sigma_2, \ldots, \sigma_n\}, \sigma_i = \max_{1\leq i\leq n}\{|\sigma_i^+|, |\sigma_i^-|\}$$

Definition 1 The system (1) is said to be exponentially passive from input,if there exists an exponential Lyapunov function $V(x_t, y_t)$,and a constant $\rho > 0$ such that for all $\mu(t)$ and $\nu(t)$,all initial conditions $x(t_0)$ and $y(t_0)$,all $t \geq t_0$,the following inequality holds:

$$\dot{V}(x_t, y_t) + \rho V(x_t, y_t) \leq 2(z_1^T(t)\mu(t) + z_2^T(t)\nu(t)), \ t \geq t_0$$

where $\dot{V}(x_t, y_t)$ denotes the total derivative of $V(x_t, y_t)$ along the state trajectories $x(t)$ and $y(t)$ of system (1).

Lemma 1 [26]. The following inequalities are true :

$$0 \leq \int_0^{y_i(t)} (f_i(s) - \delta_i^- s)ds \leq (f_i(y_i(t)) - \delta_i^- y_i(t))y_i(t) \quad (5)$$

$$0 \leq \int_0^{y_i(t)} (\delta_i^+ s - f_i(s))ds \leq (\delta_i^+ y_i(t) - f_i(y_i(t)))y_i(t) \quad (6)$$

Lemma 2 (Schur complement [25]).For any constant matrix H_1, H_2, H_3,where $H_1 = H_1^T$ and $H_2 = H_2^T > 0$.Then $H_1 + H_3^T H_2^{-1} H_3 < 0$ if and only if $\begin{bmatrix} H_1 & H_3^T \\ H_3 & -H_2 \end{bmatrix} < 0$ or $\begin{bmatrix} -H_2 & H_3 \\ H_3^T & H_1 \end{bmatrix} < 0$

III. Main results

In this section,a new exponential passivity criterion for BAM neural networks with time-varying delays system is obtained.For representation convenience,the following notations are introduced:

$$\bar{x}(t) = x(t - \varsigma(t)), \bar{y}(t) = y(t - h(t))$$

$$\bar{\Sigma}_1 = diag\left\{\frac{\delta_1^+ + \delta_1^-}{2}, \frac{\delta_2^+ + \delta_2^-}{2}, \ldots, \frac{\delta_n^+ + \delta_n^-}{2}\right\}$$
$$\bar{\Sigma}_2 = diag\{\delta_1^+\delta_1^-, \delta_2^+\delta_2^-, \ldots, \delta_n^+\delta_n^-\}$$
$$\bar{\Gamma}_1 = diag\left\{\frac{\sigma_1^+ + \sigma_1^-}{2}, \frac{\sigma_2^+ + \sigma_2^-}{2}, \ldots, \frac{\sigma_n^+ + \sigma_n^-}{2}\right\}$$
$$\bar{\Gamma}_2 = diag\{\sigma_1^+\sigma_1^-, \sigma_2^+\sigma_2^-, \ldots, \sigma_n^+\sigma_n^-\}$$

$$\xi^T(t) = \Big[x^T(t), x^T(t - \frac{\varsigma}{3}), x^T(t - \frac{2\varsigma}{3}), x^T(t - \varsigma), \bar{x}^T(t), g^T(x(t)), g^T(\bar{x}(t)), \mu^T(t), y^T(t), y^T(t - \frac{h}{3}), y^T(t - \frac{2h}{3}), y^T(t - h), \bar{y}^T(t), f^T(y(t)), f^T(\bar{y}(t)), \nu^T(t)\Big]$$

Theorem 1 Given that the Assumption 1-2 hold,the system (1) is exponentially passive if there exist symmetric positive definite matrices $P_i, Q_i, i = 1, 2, \ldots, 6, G, M$,positive diagonal matrices $W_j, j = 1, 2, 3, 4, R_1, R_2, K_i = diag\{k_{1i}, k_{2i}, \ldots, k_{ni}\}$,$L_i = diag\{l_{1i}, l_{2i}, \ldots, l_{ni}\}$ $i = 1, 2$, any symmetric matrix $T_i, i = 1, 2, 3, 4$,and a constant $\rho > 0$, such that the following LMIs hold:

$$\begin{bmatrix} E^1 & \aleph^T \bar{P}_6 & \Im^T \bar{P}_4 \\ * & -\bar{P}_6 & 0 \\ * & * & -\bar{P}_4 \end{bmatrix} < 0 \quad (7)$$

$$\begin{bmatrix} P_3 & T_1 \\ * & P_4 \end{bmatrix} > 0 \quad (8)$$

$$\begin{bmatrix} P_3 & T_2 \\ * & P_4 \end{bmatrix} > 0 \quad (9)$$

$$\begin{bmatrix} P_5 & T_3 \\ * & P_6 \end{bmatrix} > 0 \quad (10)$$

$$\begin{bmatrix} P_5 & T_4 \\ * & P_6 \end{bmatrix} > 0 \quad (11)$$

where

$$E^1 = [E_{ij}^1] \ (i, j = 1, 2, \ldots, 16)$$

$$\aleph = [-A, 0_{n\times 12n}, C, E, I], \Im = [0_{n\times 5n}, D, F, I, -B, 0_{n\times 7n}]$$

$$\bar{P}_4 = hP_4, \bar{P}_6 = \varsigma P_6$$

$$r(\varsigma_D) = \begin{cases} -(1 - \varsigma_D)e^{-\rho\varsigma}, & if\, \varsigma_D \leq 1 \\ -(1 - \varsigma_D), & if\, \varsigma_D > 1 \end{cases}$$

$$\bar{r}(h_D) = \begin{cases} -(1 - h_D)e^{-\rho h}, & if\, h_D \leq 1 \\ -(1 - h_D), & if\, h_D > 1 \end{cases}$$

$$\begin{aligned} E_{11}^1 = {} & \rho P_1 - P_1 A - AP_1 + 2\Gamma_- L_1 A - 2\Gamma^+ L_2 A + \Gamma R_2 \Gamma \\ & + G_{11} - 2G_{12}\Gamma_- + 2G_{13}\Gamma^+ + \Gamma_- G_{22}\Gamma_- - 2\Gamma_- G_{23}\Gamma^+ \\ & + \Gamma^+ G_{33}\Gamma^+ + Q_1 + Q_2 + Q_3 + \varsigma P_5 - e^{-\rho\varsigma} T_3 \\ & - 2\rho\Gamma_- L_1 + 2\rho\Gamma^+ L_2 - \bar{\Gamma}_2 W_3 \end{aligned}$$

$$\begin{aligned} E_{16}^1 = {} & -L_1 A + L_2 A + G_{12} - G_{13} - \Gamma_- G_{22} + \Gamma_- G_{23} \\ & + \Gamma^+ G_{23}^T - \Gamma^+ G_{33} + \rho L_1 - \rho L_2 + \bar{\Gamma}_1 W_3 \end{aligned}$$

$$E_{18}^1 = P_1 - \Gamma_- L_1 + \Gamma^+ L_2$$

$$E_{1,14}^1 = P_1 C - \Gamma_- L_1 C + \Gamma^+ L_2 C$$

$$E_{1,15}^1 = P_1 E - \Gamma_- L_1 E + \Gamma^+ L_2 E$$

$$E_{22}^1 = -e^{-\frac{\rho\varsigma}{3}} Q_1, E_{33}^1 = -e^{-\frac{2\rho\varsigma}{3}} Q_2$$

$$E_{44}^1 = -e^{-\rho\varsigma}(Q_3 - T_4)$$

$$\begin{aligned} E_{55}^1 = {} & r(\varsigma_D)(\Gamma R_2 \Gamma + G_{11} - 2G_{12}\Gamma_- + 2G_{13}\Gamma^+ + \Gamma_- G_{22}\Gamma_- \\ & - 2\Gamma_- G_{23}\Gamma^+ + \Gamma^+ G_{33}\Gamma^+) - \bar{\Gamma}_2 W_4 + e^{-\rho\varsigma}(T_3 - T_4) \end{aligned}$$

$$E^1_{57} = r(\varsigma_D)(G_{12}-G_{13}-\Gamma_- G_{22}+\Gamma_- G_{23}+\Gamma^+ G^T_{23}-\Gamma^+ G_{33}) + \bar{\Gamma}_1 W_4$$

$$E^1_{66} = -R_2 + G_{22} - 2G_{23} + G_{33} - W_3$$

$$E^1_{68} = L_1 - L_2, E^1_{69} = D^T P_2 - D^T K_1 \Sigma_- + D^T K_2 \Sigma^+$$

$$E^1_{6,14} = L_1 C - L_2 C + D^T K_1 - D^T K_2, E^1_{6,15} = L_1 E - L_2 E$$

$$E^1_{6,16} = -I, E^1_{77} = r(\varsigma_D)(-R_2 + G_{22} - 2G_{23} + G_{33}) - W_4$$

$$E^1_{7,9} = F^T P_2 - F^T K_1 \Sigma_- + F^T K_2 \Sigma^+$$

$$E^1_{7,14} = F^T K_1 - F^T K_2, E^1_{7,16} = -I$$

$$E^1_{88} = -2I, E^1_{8,14} = -I, E^1_{8,15} = -I$$

$$\begin{aligned} E^1_{99} = {} & \rho P_2 - P_2 B - B P_2 + 2\Sigma_- K_1 B - 2\Sigma^+ K_2 B \\ & + \Sigma R_1 \Sigma + M_{11} - 2M_{12}\Sigma_- + 2M_{13}\Sigma^+ + \Sigma_- M_{22}\Sigma_- \\ & - 2\Sigma_- M_{23}\Sigma^+ + \Sigma^+ M_{33}\Sigma^+ + Q_4 + Q_5 + Q_6 + hP_3 \\ & - e^{-\rho h} T_1 - 2\rho\Sigma_- K_1 + 2\rho\Sigma^+ K_2 - \bar{\Sigma}_2 W_1 \end{aligned}$$

$$\begin{aligned} E^1_{9,14} = {} & -B^T K_1 + B K_2 + M_{12} - M_{13} - \Sigma_- M_{22} + \Sigma_- M_{23} \\ & + \Sigma^+ M^T_{23} - \Sigma^+ M_{33} + \bar{\Sigma}_1 W_1 + \rho(K_1 - K_2) \end{aligned}$$

$$E^1_{9,16} = P_2 - \Sigma_- K_1 + \Sigma^+ K_2, E^1_{10,10} = -e^{-\frac{\rho h}{3}} Q_4$$

$$E^1_{11,11} = -e^{\frac{-2\rho h}{3}} Q_5, E^1_{12,12} = -e^{-\rho h}(Q_6 - T_2)$$

$$\begin{aligned} E^1_{13,13} = {} & \bar{r}(h_D)(\Sigma R_1 \Sigma + M_{11} - 2M_{12}\Sigma_- + 2M_{13}\Sigma^+ \\ & + \Sigma_- M_{22}\Sigma_- - 2\Sigma_- M_{23}\Sigma^+ + \Sigma^+ M_{33}\Sigma^+) \\ & - \bar{\Sigma}_2 W_2 + e^{-\rho h}(T_1 - T_2) \end{aligned}$$

$$\begin{aligned} E^1_{13,15} = {} & \bar{r}(h_D)(M_{12} - M_{13} - \Sigma_- M_{22} + \Sigma_- M_{23} + \Sigma^+ M^T_{23} \\ & - \Sigma^+ M_{33}) + \bar{\Sigma}_1 W_2 \end{aligned}$$

$$E^1_{14,14} = -R_1 + M_{22} - 2M_{23} + M_{33} - W_1$$

$$E^1_{15,15} = \bar{r}(h_D)(-R_1 + M_{22} - 2M_{23} + M_{33}) - W_2$$

$$E^1_{14,16} = K_1 - K_2, E^1_{16,16} = -2I$$

All other terms are 0.

Proof: Construct a new class of Lyapunov functional candidate as follow:

$$V(x_t, y_t) = \sum_{i=1}^{6} V_i(x_t, y_t)$$

with

$$V_1(x_t, y_t) = x^T(t) P_1 x(t) + y^T(t) P_2 y(t)$$

$$\begin{aligned} V_2(x_t, y_t) = {} & 2\sum_{i=1}^{n}\int_0^{y_i(t)} \left[k_{i1}(f_i(s) - \delta_i^- s) + k_{i2}(\delta_i^+ s - f_i(s))\right] ds \\ & + 2\sum_{i=1}^{n}\int_0^{x_i(t)} \left[l_{i1}(g_i(s) - \sigma_i^- s) + l_{i2}(\sigma_i^+ s - g_i(s))\right] ds \end{aligned}$$

$$\begin{aligned} V_3(x_t, y_t) = {} & \int_{t-h(t)}^{t} \varphi\left[y^T(s)\Sigma R_1 \Sigma y(s) - f^T(y(s)) R_1 f(y(s))\right] ds \\ & + \int_{t-\varsigma(t)}^{t} \varphi\left[x^T(s)\Gamma R_2 \Gamma x(s) - g^T(x(s)) R_2 g(x(s))\right] ds \end{aligned}$$

$$\begin{aligned} V_4(x_t, y_t) = {} & \int_{t-h(t)}^{t} \varphi \begin{bmatrix} y(s) \\ f(y(s)) - \Sigma_- y(s) \\ \Sigma^+ y(s) - f(y(s)) \end{bmatrix}^T M \begin{bmatrix} y(s) \\ f(y(s)) - \Sigma_- y(s) \\ \Sigma^+ y(s) - f(y(s)) \end{bmatrix} ds \\ & - \int_{t-\varsigma(t)}^{t} \varphi \begin{bmatrix} x(s) \\ g(x(s)) - \Gamma_- x(s) \\ \Gamma^+ x(s) - g(x(s)) \end{bmatrix}^T G \begin{bmatrix} x(s) \\ g(x(s)) - \Gamma_- x(s) \\ \Gamma^+ x(s) - g(x(s)) \end{bmatrix} ds \end{aligned}$$

$$\begin{aligned} V_5(x_t, y_t) = {} & \int_{t-\frac{h}{3}}^{t} \varphi y^T(s) Q_4 y(s) ds + \int_{t-\frac{2h}{3}}^{t} \varphi y^T(s) Q_5 y(s) ds \\ & + \int_{t-h}^{h} \varphi y^T(s) Q_6 y(s) ds + \int_{t-\frac{\varsigma}{3}}^{t} \varphi x^T(s) Q_1 x(s) ds \\ & + \int_{t-\frac{2\varsigma}{3}}^{t} \varphi x^T(s) Q_2 x(s) ds + \int_{t-\varsigma}^{t} \varphi x^T(s) Q_3 x(s) ds \end{aligned}$$

$$\begin{aligned} V_6(x_t, y_t) = {} & \int_{-h}^{0}\int_{t+\theta}^{t} \varphi(y^T(s) P_3 y(s) + \dot{y}^T(s) P_4 \dot{y}(s)) ds \\ = {} & \int_{-\varsigma}^{0}\int_{t+\theta}^{t} \varphi(x^T(s) P_5 x(s) + \dot{x}^T(s) P_6 \dot{x}(s)) ds \end{aligned}$$

where

$$\varphi = e^{-\rho(t-s)}$$

$$M = \begin{bmatrix} M_{11} & M_{12} & M_{13} \\ * & M_{22} & M_{23} \\ * & * & M_{33} \end{bmatrix}, G = \begin{bmatrix} G_{11} & G_{12} & G_{13} \\ * & G_{22} & G_{23} \\ * & * & G_{33} \end{bmatrix}$$

Then, taking the derivative of $V(x_t, y_t)$ with respect to t along the system (1) yields

$$\dot{V}_1(x_t, y_t) = 2x^T(t) P_1 \dot{x}(t) + 2y^T(t) P_2 \dot{y}(t) \tag{12}$$

$$\begin{aligned} \dot{V}_2(x_t, y_t) = {} & 2(f^T(y(t)) - y^T(t)\Sigma_-) K_1 \dot{y}(t) \\ & + 2(y^T(t)\Sigma^+ - f^T(y(t))) K_2 \dot{y}(t) \\ & + 2(g^T(x(t)) - x^T(t)\Gamma_-) L_1 \dot{x}(t) \\ & + 2(x^T(t)\Gamma^+ - g^T(x(t))) L_2 \dot{x}(t) \end{aligned} \tag{13}$$

$$\begin{aligned} \dot{V}_3(x_t, y_t) \le {} & -\rho V_3 + x^T(t)\Gamma R_2 \Gamma x(t) - g^T(x(t)) R_2 g(x(t)) \\ & + r(\varsigma_D)[\bar{x}^T(t)\Gamma R_2 \Gamma \bar{x}(t) - g^T(\bar{x}(t)) R_2 g(\bar{x}(t))] \\ & + y^T(t)\Sigma R_1 \Sigma y(t) - f^T(y(t)) R_1 f(y(t)) \\ & + \bar{r}(h_D)[\bar{y}^T(t)\Sigma R_1 \Sigma \bar{y}(t) - f^T(\bar{y}(t)) R_1 f(\bar{y}(t))] \end{aligned} \tag{14}$$

$$\begin{aligned}\dot{V}_4(x_t,y_t)\leq&-\rho V_4+\begin{bmatrix}x(t)\\g(x(t))-\Gamma_-x(t)\\\Gamma^+x(t)-g(x(t))\end{bmatrix}^TG\begin{bmatrix}x(t)\\g(x(t))-\Gamma_-x(t)\\\Gamma^+x(t)-g(x(t))\end{bmatrix}\\&+r(\varsigma_D)\begin{bmatrix}\bar{x}(t)\\g(\bar{x}(t))-\Gamma_-\bar{x}(t)\\\Gamma^+\bar{x}(t)-g(\bar{x}(t))\end{bmatrix}^TG\begin{bmatrix}\bar{x}(t)\\g(\bar{x}(t))-\Gamma_-\bar{x}(t)\\\Gamma^+\bar{x}(t)-g(\bar{x}(t))\end{bmatrix}\\&+\begin{bmatrix}y(t)\\f(y(t))-\Sigma_-y(t)\\\Sigma^+y(t)-f(y(t))\end{bmatrix}^TM\begin{bmatrix}y(t)\\f(y(t))-\Sigma_-y(t)\\\Sigma^+y(t)-f(y(t))\end{bmatrix}\\&+\bar{r}(h_D)\begin{bmatrix}\bar{y}(t)\\f(\bar{y}(t))-\Sigma_-\bar{y}(t)\\\Sigma^+\bar{y}(t)-f(\bar{y}(t))\end{bmatrix}^TM\begin{bmatrix}\bar{y}(t)\\f(\bar{y}(t))-\Sigma_-\bar{y}(t)\\\Sigma^+\bar{y}(t)-f(\bar{y}(t))\end{bmatrix}\end{aligned}\tag{15}$$

$$\begin{aligned}\dot{V}_5(x_t,y_t)=&-\rho V_5+x^T(t)(Q_1+Q_2+Q_3)x(t)\\&-e^{-\frac{\rho\varsigma}{3}}x^T(t-\frac{\varsigma}{3})Q_1x(t-\frac{\varsigma}{3})\\&-e^{-\frac{2\rho\varsigma}{3}}x^T(t-\frac{2\varsigma}{3})Q_2x(t-\frac{2\varsigma}{3})\\&-e^{-\rho\varsigma}x^T(t-\varsigma)Q_3x(t-\varsigma)\\&+y^T(t)(Q_4+Q_5+Q_6)y(t)\\&-e^{-\frac{\rho h}{3}}y^T(t-\frac{h}{3})Q_4y(t-\frac{h}{3})\\&-e^{-\frac{2\rho h}{3}}y^T(t-\frac{2h}{3})Q_5y(t-\frac{2h}{3})\\&-e^{-\rho h}y^T(t-h)Q_6y(t-h)\end{aligned}\tag{16}$$

$$\begin{aligned}\dot{V}_6(x_t,y_t)\leq&-\rho V_6+h(y^T(t)P_3y(t)+\dot{y}(t)P_4\dot{y}(t))\\&+\varsigma(x^T(t)P_5x(t)+\dot{x}^T(t)P_6\dot{x}(t))\\&-e^{-\rho h}\int_{t-h}^{t}(y^T(s)P_3y(s)+\dot{y}(s)P_4\dot{y}(s))ds\\&-e^{-\rho\varsigma}\int_{t-\varsigma}^{t}(x^T(s)P_5x(s)+\dot{x}^T(s)P_6\dot{x}(s))ds\end{aligned}\tag{17}$$

Now,we consider the following four zero equalities with any symmetric matrix T_1,T_2,T_3,T_4

$$y^T(t)T_1y(t)-\bar{y}^T(t)T_1\bar{y}(t)-2\int_{t-h(t)}^{t}y^T(s)T_1\dot{y}(s)ds=0\tag{18}$$

$$\bar{y}^T(t)T_2\bar{y}(t)-y^T(t-h)T_2y(t-h)-2\int_{t-h}^{t-h(t)}y^T(s)T_2\dot{y}(s)ds=0\tag{19}$$

$$x^T(t)T_3x(t)-\bar{x}^T(t)T_3\bar{x}(t)-2\int_{t-\varsigma(t)}^{t}x^T(s)T_3\dot{x}(s)ds=0\tag{20}$$

$$\bar{x}^T(t)T_4\bar{x}(t)-x^T(t-\varsigma)T_4x(t-\varsigma)-2\int_{t-\varsigma}^{t-\varsigma(t)}x^T(s)T_4\dot{x}(s)ds=0\tag{21}$$

Here,using Lemma 1,we have

$$\begin{aligned}&\sum_{i=1}^{n}\int_0^{y_i(t)}\big[k_{i1}(f_i(s)-\delta_i^-s)+k_{i2}(\delta_i^+s-f_i(s))\big]ds\\&\leq(f(y(t))-\Sigma_-y(t))^TK_1y(t)+(\Sigma^+y(t)-f(y(t)))^TK_2y(t)\end{aligned}\tag{22}$$

$$\begin{aligned}&\sum_{i=1}^{n}\int_0^{x_i(t)}\big[l_{i1}(g_i(s)-\sigma_i^-s)+l_{i2}(\sigma_i^+s-g_i(s))\big]ds\\&\leq(g(x(t))-\Gamma_-x(t))^TL_1x(t)+(\Gamma^+x(t)-g(x(t)))^TL_2x(t)\end{aligned}\tag{23}$$

From (3), we can get that there exist positive diagonal matrices W_1,W_2,W_3,W_4 such that the following inequalities holds:

$$\begin{bmatrix}y(t)\\f(y(t))\end{bmatrix}^T\begin{bmatrix}-\bar{\Sigma}_2W_1&\bar{\Sigma}_1W_1\\*&-W_1\end{bmatrix}\begin{bmatrix}y(t)\\f(y(t))\end{bmatrix}\geq0\tag{24}$$

$$\begin{bmatrix}\bar{y}(t)\\f(\bar{y}(t))\end{bmatrix}^T\begin{bmatrix}-\bar{\Sigma}_2W_2&\bar{\Sigma}_1W_2\\*&-W_2\end{bmatrix}\begin{bmatrix}\bar{y}(t)\\f(\bar{y}(t))\end{bmatrix}\geq0\tag{25}$$

$$\begin{bmatrix}x(t)\\g(x(t))\end{bmatrix}^T\begin{bmatrix}-\bar{\Gamma}_2W_3&\bar{\Gamma}_1W_3\\*&-W_3\end{bmatrix}\begin{bmatrix}x(t)\\g(x(t))\end{bmatrix}\geq0\tag{26}$$

$$\begin{bmatrix}\bar{x}(t)\\g(\bar{x}(t))\end{bmatrix}^T\begin{bmatrix}-\bar{\Gamma}_2W_4&\bar{\Gamma}_1W_4\\*&-W_4\end{bmatrix}\begin{bmatrix}\bar{x}(t)\\g(\bar{x}(t))\end{bmatrix}\geq0\tag{27}$$

From (12)-(27),we can get

$$\begin{aligned}&\dot{V}(x_t,y_t)+\rho V(x_t,y_t)-2z_1^T(t)\mu(t)-2z_2^T(t)\nu(t)\\&\leq\xi^T(t)(E^1+\aleph^T\bar{P}_6\aleph+\Im^T\bar{P}_4\Im)\xi(t)\\&-\int_{t-h(t)}^{t}\begin{bmatrix}y(s)\\\dot{y}(s)\end{bmatrix}^T\begin{bmatrix}P_3&T_1\\*&P_4\end{bmatrix}\begin{bmatrix}y(s)\\\dot{y}(s)\end{bmatrix}ds\\&-\int_{t-h}^{t-h(t)}\begin{bmatrix}y(s)\\\dot{y}(s)\end{bmatrix}^T\begin{bmatrix}P_3&T_2\\*&P_4\end{bmatrix}\begin{bmatrix}y(s)\\\dot{y}(s)\end{bmatrix}ds\\&-\int_{t-\varsigma(t)}^{t}\begin{bmatrix}x(s)\\\dot{x}(s)\end{bmatrix}^T\begin{bmatrix}P_5&T_3\\*&P_6\end{bmatrix}\begin{bmatrix}x(s)\\\dot{x}(s)\end{bmatrix}ds\\&-\int_{t-\varsigma}^{t-\varsigma(t)}\begin{bmatrix}x(s)\\\dot{x}(s)\end{bmatrix}^T\begin{bmatrix}P_5&T_4\\*&P_6\end{bmatrix}\begin{bmatrix}x(s)\\\dot{x}(s)\end{bmatrix}ds\end{aligned}$$

Using Lemma 2,and (7)-(11),we can get

$$\dot{V}(x_t,y_t)+\rho V(x_t,y_t)\leq2z_1^T(t)\mu(t)-2z_2^T(t)\nu(t)$$

Based on Definition 1, the system (1) is guaranteed to be exponential passivity,which complete the proof. ■

Remark 1 Firstly,in this paper,the restriction that the derivative of a time-varying delay be less than 1 is removed.Secondly,dividing the delay interval $[0,h]$ and $[0,\varsigma]$ into three different ones $[0,\frac{h}{3}],[\frac{h}{3},\frac{2h}{3}],[\frac{2h}{3},h]$ and $[0,\frac{\varsigma}{3}],[\frac{\varsigma}{3},\frac{2\varsigma}{3}],[\frac{2\varsigma}{3},\varsigma]$,respectively,and constructing new Lyapunov functional which contains some new integral terms.It have potential to yield less conservative results.

Remark 2 Theorem 1 reduces to the LMIs exponential stabil ity condition for delayed BAM neural networks if the $\mu(t)=0$ and $\nu(t)=0$.

Next,we consider the special case of the system (1) with $\mu(t) = 0, \nu(t) = 0$.

Corollary 1 Given that the Assumption 1-2 hold,the system (1) is exponentially passive if there exist symmetric positive definite matrices $P_i, Q_i, i = 1, 2, \ldots, 6, G, M$,positive diagonal matrices $W_j, j = 1, 2, 3, 4, R_1, R_2, K_i = diag\{k_{1i}, k_{2i}, \ldots, k_{ni}\}, L_i = diag\{l_{1i}, l_{2i}, \ldots, l_{ni}\}$ $i = 1, 2$, any symmetric matrix $T_i, i = 1, 2, 3, 4$ and a constant $\rho > 0$ such that the following LMIs hold:

$$\begin{bmatrix} F^1 & \aleph_1^T \bar{P}_6 & \Im_1^T \bar{P}_4 \\ * & -\bar{P}_6 & 0 \\ * & * & -\bar{P}_4 \end{bmatrix} < 0 \tag{28}$$

$$\begin{bmatrix} P_3 & T_1 \\ * & P_4 \end{bmatrix} > 0 \tag{29}$$

$$\begin{bmatrix} P_3 & T_2 \\ * & P_4 \end{bmatrix} > 0 \tag{30}$$

$$\begin{bmatrix} P_5 & T_3 \\ * & P_6 \end{bmatrix} > 0 \tag{31}$$

$$\begin{bmatrix} P_5 & T_4 \\ * & P_6 \end{bmatrix} > 0 \tag{32}$$

where

$$\aleph_1 = [-A, 0_{n\times 11n}, C, E], \Im_1 = [0_{n\times 5n}, D, F, -B, 0_{n\times 6n}]$$

$$F^1 = [F^1_{ij}] \ \ (i, j = 1, 2, \ldots, 14)$$

$$\begin{aligned} F^1_{11} &= \rho P_1 - P_1 A - A P_1 + 2\Gamma_- L_1 A - 2\Gamma^+ L_2 A + \Gamma R_2 \Gamma \\ &+ G_{11} - 2G_{12}\Gamma_- + 2G_{13}\Gamma^+ + \Gamma_- G_{22}\Gamma_- - 2\Gamma_- G_{23}\Gamma^+ \\ &+ \Gamma^+ G_{33}\Gamma^+ + Q_1 + Q_2 + Q_3 + \varsigma P_5 - e^{-\rho\varsigma} T_3 \\ &- 2\rho\Gamma_- L_1 + 2\rho\Gamma^+ L_2 - \bar{\Gamma}_2 W_3 \end{aligned}$$

$$\begin{aligned} F^1_{16} &= -L_1 A + L_2 A + G_{12} - G_{13} - \Gamma_- G_{22} + \Gamma_- G_{23} \\ &+ \Gamma^+ G_{23}^T - \Gamma^+ G_{33} + \rho L_1 - \rho L_2 + \bar{\Gamma}_1 W_3 \end{aligned}$$

$$F^1_{1,13} = P_1 C - \Gamma_- L_1 C + \Gamma^+ L_2 C$$

$$F^1_{1,14} = P_1 E - \Gamma_- L_1 E + \Gamma^+ L_2 E$$

$$F^1_{22} = -e^{-\frac{\rho\varsigma}{3}} Q_1, F^1_{33} = -e^{-\frac{2\rho\varsigma}{3}} Q_2$$

$$F^1_{44} = -e^{-\rho\varsigma}(Q_3 - T_4)$$

$$\begin{aligned} F^1_{55} &= r(\varsigma_D)(\Gamma R_2 \Gamma + G_{11} - 2G_{12}\Gamma_- + 2G_{13}\Gamma^+ + \Gamma_- G_{22}\Gamma_- \\ &- 2\Gamma_- G_{23}\Gamma^+ + \Gamma^+ G_{33}\Gamma^+) - \bar{\Gamma}_2 W_4 + e^{-\rho\varsigma}(T_3 - T_4) \end{aligned}$$

$$\begin{aligned} F^1_{57} &= r(\varsigma_D)(G_{12} - G_{13} - \Gamma_- G_{22} + \Gamma_- G_{23} + \Gamma^+ G_{23}^T - \Gamma^+ G_{33}) \\ &+ \bar{\Gamma}_1 W_4 \end{aligned}$$

$$F^1_{66} = -R_2 + G_{22} - 2G_{23} + G_{33} - W_3$$

$$F^1_{6,13} = L_1 C - L_2 C + D^T K_1 - D^T K_2, F^1_{6,14} = L_1 E - L_2 E$$

$$F^1_{77} = r(\varsigma_D)(-R_2 + G_{22} - 2G_{23} + G_{33}) - W_4$$

$$F^1_{78} = F^T P_2 - F^T K_1 \Sigma_- + F^T K_2 \Sigma^+$$

$$F^1_{7,13} = F^T K_1 - F^T K_2$$

$$\begin{aligned} F^1_{88} &= \rho P_2 - P_2 B - B P_2 + 2\Sigma_- K_1 B - 2\Sigma^+ K_2 B \\ &+ \Sigma R_1 \Sigma + M_{11} - 2M_{12}\Sigma_- + 2M_{13}\Sigma^+ + \Sigma_- M_{22}\Sigma_- \\ &- 2\Sigma_- M_{23}\Sigma^+ + \Sigma^+ M_{33}\Sigma^+ + Q_4 + Q_5 + Q_6 + hP_3 \\ &- e^{-\rho h} T_1 - 2\rho\Sigma_- K_1 + 2\rho\Sigma^+ K_2 - \bar{\Sigma}_2 W_1 \end{aligned}$$

$$\begin{aligned} F^1_{8,13} &= -B^T K_1 + B K_2 + M_{12} - M_{13} - \Sigma_- M_{22} + \Sigma_- M_{23} \\ &+ \Sigma^+ M_{23}^T - \Sigma^+ M_{33} + \bar{\Sigma}_1 W_1 + \rho(K_1 - K_2) \end{aligned}$$

$$F^1_{8,14} = P_2 - \Sigma_- K_1 + \Sigma^+ K_2, F^1_{9,9} = -e^{-\frac{\rho h}{3}} Q_4$$

$$F^1_{10,10} = -e^{\frac{-2\rho h}{3}} Q_5, F^1_{11,11} = -e^{-\rho h}(Q_6 - T_2)$$

$$\begin{aligned} F^1_{12,12} &= \bar{r}(h_D)(\Sigma R_1 \Sigma + M_{11} - 2M_{12}\Sigma_- + 2M_{13}\Sigma^+ \\ &+ \Sigma_- M_{22}\Sigma_- - 2\Sigma_- M_{23}\Sigma^+ + \Sigma^+ M_{33}\Sigma^+) \\ &- \bar{\Sigma}_2 W_2 + e^{-\rho h}(T_1 - T_2) \end{aligned}$$

$$\begin{aligned} F^1_{12,14} &= \bar{r}(h_D)(M_{12} - M_{13} - \Sigma_- M_{22} + \Sigma_- M_{23} + \Sigma^+ M_{23}^T \\ &- \Sigma^+ M_{33}) + \bar{\Sigma}_1 W_2 \end{aligned}$$

$$F^1_{13,13} = -R_1 + M_{22} - 2M_{23} + M_{33} - W_1$$

$$F^1_{14,14} = \bar{r}(h_D)(-R_1 + M_{22} - 2M_{23} + M_{33}) - W_2$$

All other terms are 0.

Proof: The proof of the Corollary 1 is consequence of Theorem 1 by choosing $\mu(t) = 0, \nu(t) = 0$.Hence the proof is omitted. ■

Remark 3 In this paper,Theorem 1 and Corollary 1 require the upper bound h_D, ς_D to be known.However,in many cases h_D, ς_D is unknown,considering this situation ,we can set $R_i = 0, (i = 1, 2), M = G = 0$ in $V(x_t, y_t)$,and employ the same methods in Theorem 1 and Corollary 1,we can derive the delay-dependent and delay-derivative-independent exponential passivity criteria.

IV. Example

In this section,we provide a example to demonstrate the effectiveness and feasibility of our results.

Example 1 Consider the BAM neural networks with the following parameters:

$$A=\begin{bmatrix}1.8 & 0\\ 0 & 2.2\end{bmatrix}, B=\begin{bmatrix}2.5 & 0\\ 0 & 2.2\end{bmatrix}, C=\begin{bmatrix}-1 & 0\\ -1 & -1\end{bmatrix},$$
$$D=\begin{bmatrix}0.1 & 0\\ 0 & -0.1\end{bmatrix}, E=\begin{bmatrix}0.9 & 0.1\\ 0.1 & 0.5\end{bmatrix}, F=\begin{bmatrix}0.3 & 0.1\\ 0.1 & 0.4\end{bmatrix},$$
$$\Sigma^{+}=diag\{0.1,0.1\}, \Sigma^{-}=diag\{-0.1,-0.1\},$$
$$\Gamma^{+}=diag\{1,1\}, \Gamma^{-}=diag\{-1,-1\},$$

and $f_1(s)=\tanh(-0.7s), f_2(s)=\tanh(0.2s)$,
$g_1(s)=\tanh(-0.2s), g_2(s)=\tanh(-0.8s)$
$h(t)=0.8|\cos t|, \varsigma(t)=0.8|\sin t|$.
In Table I,we consider the case of $h=\varsigma=n_1, h_D=\varsigma_D=n_2$,the upper bound of ρ is derived by Theorem 1 and Corollary 1.According to Table II,we can know the maximum values of ρ for various h,ς,and unknown h_D,ς_D.By using the Matlab LMI toolbox,we solve LMIs (7)-(11),for the case of $h=\varsigma=0.6, \varsigma_D=h_D=0.7, \rho=1.028$,and obtain

$$P_1=\begin{bmatrix}2.9045 & -0.0637\\ -0.0637 & 3.1610\end{bmatrix}, P_2=\begin{bmatrix}0.7688 & 0.1800\\ 0.1800 & 0.4953\end{bmatrix},$$
$$P_3=\begin{bmatrix}0.4171 & 0.2033\\ 0.2033 & 0.1061\end{bmatrix}, P_4=\begin{bmatrix}0.2005 & 0.1067\\ 0.1067 & 0.0829\end{bmatrix},$$
$$P_5=\begin{bmatrix}0.4354 & -0.1857\\ -0.1857 & 2.8541\end{bmatrix}, P_6=\begin{bmatrix}1.5861 & 0.1032\\ 0.1032 & 0.2407\end{bmatrix},$$

$$Q_1=\begin{bmatrix}0.0011 & -0.0130\\ -0.0130 & 0.1691\end{bmatrix}, Q_2=\begin{bmatrix}0.0113 & -0.0011\\ -0.0011 & 0.1691\end{bmatrix},$$
$$Q_3=\begin{bmatrix}0.8193 & -0.0038\\ -0.0038 & 0.8689\end{bmatrix}, Q_4=\begin{bmatrix}0.1185 & 0.0571\\ 0.0571 & 0.0279\end{bmatrix},$$
$$Q_5=\begin{bmatrix}0.1183 & 0.0274\\ 0.0274 & 0.0450\end{bmatrix}, Q_6=\begin{bmatrix}0.0808 & 0.0389\\ 0.0389 & 0.0190\end{bmatrix},$$

$$K_1=\begin{bmatrix}0.0027 & 0\\ 0 & 0.0027\end{bmatrix}, K_2=\begin{bmatrix}0.0026 & 0\\ 0 & 0.0026\end{bmatrix},$$
$$R_1=\begin{bmatrix}0.3472 & 0\\ 0 & 0.3472\end{bmatrix}, R_2=\begin{bmatrix}0.7006 & 0\\ 0 & 0.7006\end{bmatrix},$$
$$L_1=1.0\times 10^{-3}\times\begin{bmatrix}0.1101 & 0\\ 0 & 0.1101\end{bmatrix},$$
$$L_2=1.0\times 10^{-3}\times\begin{bmatrix}0.1094 & 0\\ 0 & 0.1094\end{bmatrix},$$

$$M=\begin{bmatrix}0.0011 & -0.0130 & 0.1691\\ -0.0130 & 0.0011 & -0.0130\\ 0.1691 & -0.0130 & 0.1691\end{bmatrix},$$
$$G=\begin{bmatrix}0.4354 & -0.1857 & 2.8541\\ -0.1857 & 1.5861 & 0.1032\\ 2.8541 & 0.1032 & 0.2407\end{bmatrix},$$

The state trajectories of variables $x(t)$ and $y(t)$ with the initial condition $x^T(t)=[1,-1]^T$ and $y^T(t)=[2,-2]^T$ are shown in Fig.1.

TABLE I
Maximum value of ρ with different n_1, n_2 in Example 1

Method	Theorem 1	Corollary 1
$n_1=0.1, n_2=0.4$	1.467	3.557
$n_1=0.4, n_2=0.4$	1.159	3.230
$n_1=0.6, n_2=0.7$	1.028	3.113
$n_1=0.8, n_2=0.9$	0.921	2.979

TABLE II
Maximum value of ρ with different h, ς, unknown h_D, ς_D in Example 1

Method	Theorem 1	Corollary 1
$h=0.1, \varsigma=0.3$	1.183	3.703
$h=0.3, \varsigma=0.3$	1.178	3.000
$h=0.5, \varsigma=0.4$	1.107	2.816
$h=0.7, \varsigma=0.8$	0.886	2.448

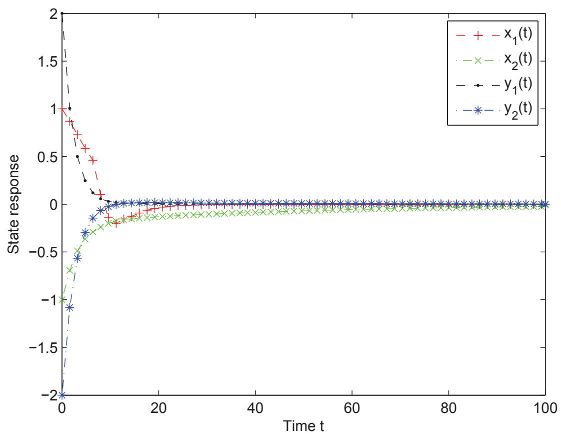

Fig.1. The state response of system (1) in Example 1.

V. Conclusion

In this paper,the issues of delay-dependent exponential passivity analysis is investigated for BAM neural networks with time-varying delays.The obtained criteria are less conservative because a bounding technique of integral terms with free-weighting matrices in different delay intervals is utilized. Finally,for this problem,one example is provided to show the feasibility of the proposed criteria in this paper.

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