LMI-based criterion for global asymptotic stability of BAM neural networks with time delays

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Abstract: This paper presents a stability criterion for global asymptotic stability of the equilibrium point for Bidirectional Associative Memory (BAM) neural networks with fixed time delays. An approach combining the Lyapunov-Krasovskii functional with Linear Matrix Inequality (LMI) is taken to investigate the stability of the system. A delay-dependent LMI criterion is derived. Finally, a numerical example is given to illustrate the results.

Keywords: BAM neural networks; LMI; asymptotic stability; delay.


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1 Introduction

Bidirectional Associative Memory (BAM) neural networks are a class of important neural network with the ability to store a collection of pattern pairs via unsupervised learning, which have applications in pattern recognition, artificial intelligence, and automatic control (Kosko, 1987, 1988). Thus, the BAM neural networks has been one of the most interesting research topics and has attracted the attention of many researchers (Gopalsamy and He, 1994; Cao and Wang, 2000; Guo et al., 2003). As is well known, both in biological and man-made neural networks, the delays arise because of the processing of information. More specifically, the delays occur in the communication and response of neurons owing to the finite switching speed of amplifiers in the electronic implementation of analog neural networks. The delay is a source of instability and oscillatory response of the networks. Therefore, the study of the stability problem of BAM with delays has raised considerable interest (Liao and Yu, 1998; Zhang and Yang, 2001; Zhao, 2002; Cao, 2003; Chen et al., 2003; Park, 2006; Huang et al., 2005).

In this paper, we investigate the problem of stability analysis for BAM neural networks with fixed time delays. Attention is focused on the derivation of a novel criterion which guarantees the global asymptotic stability of the equilibrium point of the BAM neural network. The criterion developed in this paper is expressed by several LMIs, which can be solved numerically very efficiently by various convex optimisation algorithms (Boyd et al., 1994) and no tuning of parameters are involved.

The rest of this paper is organised as follows: in Section 2, the problem to be investigated is stated; in Section 3, a new stability criterion for asymptotic stability of BAM with delays will be established; in Section 4, some conclusions are drawn.

In this paper, we use $X^T, X^{-1}$ to denote respectively the transpose of a vector (or matrix) and the inverse of a square matrix. $\mathbb{R}^n$ denotes the $n$ dimensional Euclidean space, and $\mathbb{R}^{n \times m}$ is the set of all $n \times m$ real matrices. $I$ denotes the identity matrix with appropriate dimensions. $\star$ denotes the elements below the main diagonal of a symmetric block matrix. $\text{diag}\{\cdots\}$ denotes the diagonal matrix. For symmetric matrices $X$ and $Y$, the notation $X > Y$ (respectively, $X \geq Y$) means that the matrix $X - Y$ is positive definite, (respectively, nonnegative).

2 Problem statement

Consider the following BAM neural networks with constant delays:

$$
\dot{u}_i(t) = -a_i u_i(t) + \sum_{j=1}^{m} w_{ji} g_j(v_j(t - \tau)) + I_i, \quad i = 1, 2, \ldots, n,
$$

$$
\dot{v}_j(t) = -b_j v_j(t) + \sum_{i=1}^{n} v_{ij} g_i(u_i(t - \sigma)) + J_j, \quad j = 1, 2, \ldots, m,
$$

(1)
in which \( u = (u_1, u_2, \ldots, u_n)^T \in \mathbb{R}^n \) and \( v = (v_1, v_2, \ldots, v_m)^T \in \mathbb{R}^m \) are the activations of the \( i \)th neurons and the \( j \)th neurons, respectively, \( w_{ji} \) and \( v_{ij} \) are the connection weights at the time \( t \), \( I_i \) and \( J_j \) denote the external inputs, \( r > 0 \) and \( \sigma > 0 \) are positive constants which correspond to the finite speed of axonal signal transmission, and \( a_i > 0, b_j > 0 \).

In this paper, it is assumed that the activate functions \( g_i \) possess the following properties:

(A1) \( g_i \) is bounded on \( \mathcal{R}, i = 1, 2, \ldots, \max\{m, n\} \).

(A2) There exist real numbers \( M_i > 0 \) such that \( |g_i(x) - g_i(y)| \leq M_i|x - y| \) for any \( x, y \in \mathcal{R}, i = 1, 2, \ldots, \max\{m, n\} \).

It is clear that under the assumption (A1) and (A2), system (3) has at least one equilibrium point of the system, then we will shift the equilibrium points to the origin by the transformation \( x_i(t) = u_i(t) - u^*_i, y_j(t) = v_j(t) - v^*_j, f_i(x_i(t)) = g_i(u_i(t)) - g_i(u^*_i) \), and \( f_j(y_j(t)) = g_j(v_j(t)) - g_j(v^*_j) \). Then, the transformed system is as follows:

\[
\begin{align*}
\dot{x}_i(t) &= -a_ix_i(t) + \sum_{j=1}^{m} w_{ji}f_j(y_j(t - \tau)), \quad i = 1, 2, \ldots, n, \\
\dot{y}_j(t) &= -b_jy_j(t) + \sum_{i=1}^{n} v_{ij}f_i(x_i(t - \sigma)), \quad j = 1, 2, \ldots, m, \\
x_i(s) &= \phi_i(s), \quad y_j(s) = \psi_j(s), \quad s \in [-\max\{\tau, \sigma\}, 0], \\
&\quad i = 1, 2, \ldots, n, \quad j = 1, 2, \ldots, m,
\end{align*}
\]

(2)

where the activate functions \( f_i \) satisfy the following properties:

(H1) \( f_i \) is bounded on \( \mathcal{R}, i = 1, 2, \ldots, \max\{m, n\} \).

(H2) There exist real numbers \( M_i > 0 \) such that \( |f_i(x) - f_i(y)| \leq M_i|x - y| \) for any \( x, y \in \mathcal{R}, i = 1, 2, \ldots, \max\{m, n\} \).

(H3) \( f_i(0) = 0, \quad i = 1, 2, \ldots, \max\{m, n\} \).

For convenience, we can rewrite (2) in the form:

\[
\begin{align*}
\dot{x}(t) &= -Ax(t) + W^Tf(y(t - \tau)), \\
\dot{y}(t) &= -By(t) + V^T\bar{f}(x(t - \sigma)),
\end{align*}
\]

(3)

where \( x(t) = (x_1(t), x_2(t), \ldots, x_n(t))^T, y(t) = (y_1(t), y_2(t), \ldots, y_m(t))^T, A = \text{diag}(a_1, a_2, \ldots, a_n), B = \text{diag}(b_1, b_2, \ldots, b_m), W = (w_{ij})_{m \times n}, V = (v_{ij})_{n \times m}, \bar{f} = (f_1, f_2, \ldots, f_m)^T, \bar{f} = (f_1, f_2, \ldots, f_m)^T, M = \text{diag}\{M_1, M_2, \ldots, M_m\}, \text{and } \overline{M} = \text{diag}\{M_1, M_2, \ldots, M_m\} \).

3 Main result

In this section, we present a stability criterion for global asymptotic stability of system (3).
The following fact and lemmas will be used for deriving main result.

**Fact 1:** (Schur complement) Given constant symmetric matrices $\Sigma_1, \Sigma_2, \Sigma_3$ where $\Sigma_1 = \Sigma_1^T$ and $0 < \Sigma_2 = \Sigma_2^T$, then $\Sigma_1 + \Sigma_3^T \Sigma_2^{-1} \Sigma_3 < 0$ if and only if

$$
\begin{bmatrix}
\Sigma_1 & \Sigma_3^T \\
\Sigma_3 & -\Sigma_2
\end{bmatrix} < 0, \quad \text{or} \quad
\begin{bmatrix}
-\Sigma_2 & \Sigma_3 \\
\Sigma_3^T & \Sigma_1
\end{bmatrix} < 0.
$$

(4)

**Lemma 2** (Moon et al., 2001): Assume that $a \in \mathbb{R}^n$, $b \in \mathbb{R}^m$, and $N \in \mathbb{R}^{n \times m}$ are defined, then for any matrices $X \in \mathbb{R}^{n \times n}$, $Y \in \mathbb{R}^{n \times m}$ and $Z \in \mathbb{R}^{m \times m}$, the following holds

$$
-2a^T nb \leq a^T \begin{bmatrix} X & Y-N \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix}, \quad X \begin{bmatrix} a & Y \end{bmatrix} \geq 0.
$$

(5)

**Lemma 3** (Cao et al., 1998): For any $z, y \in \mathbb{R}^{n \times m}$, a positive scalar $\epsilon$, and any positive definite matrix $X \in \mathbb{R}^{n \times n}$ the following inequality

$$
2z^T y \leq \epsilon z^T X^{-1} z + \epsilon^{-1} y^T X y
$$

holds.

Now, we have the following theorem.

**Theorem 4:** For given $\tau$ and $\sigma$, the equilibrium point of system (3) is globally asymptotically stable if there exist positive definite matrices $P, Q, S_1, S_2, X_1, X_2, Z_1, Z_2, P_i, Q_i$, positive diagonal matrices $D = \text{diag}\{d_1, \ldots, d_n\}$, $E = \text{diag}\{e_1, \ldots, e_m\}$, positive scalars $\epsilon_1, \epsilon_2$ and $R_1 \geq 0, R_2 \geq 0$, satisfying the following LMIs:

$$
\begin{bmatrix}
\Pi_1 & 0 & R_1^T & \Pi_3 & 0 & 0 \\
\ast & -2DAM^{-1} & 0 & 0 & DW^T & 0 \\
\ast & \ast & \Pi_2 & 0 & 0 & V \\
\ast & \ast & \ast & \ast & \Pi_4 & 0 \\
\ast & \ast & \ast & \ast & -P_2 & 0 \\
\ast & \ast & \ast & \ast & \ast & -\epsilon_2 I
\end{bmatrix} < 0,
$$

(7)

$$
\begin{bmatrix}
\Pi_5 & 0 & R_2^T & \Pi_7 & 0 & 0 \\
\ast & -2EBM^{-1} & 0 & 0 & EV^T & 0 \\
\ast & \ast & \Pi_6 & 0 & 0 & W \\
\ast & \ast & \ast & \ast & \Pi_8 & 0 \\
\ast & \ast & \ast & \ast & -Q_2 & 0 \\
\ast & \ast & \ast & \ast & \ast & -\epsilon_1 I
\end{bmatrix} < 0,
$$

$$
(X_1 \begin{bmatrix} R_1 \\ Z_1 \end{bmatrix}) > 0, \quad (X_2 \begin{bmatrix} R_2 \\ Z_2 \end{bmatrix}) > 0,
$$
where

\[
\Pi_1 = -PA - AP + M S_1 M + \sigma A^T Z_1 A,
\]
\[
\Pi_2 = -S_1 + \sigma X_1 - R_1 M^{-1} - M^{-1} R_1^T + Q_1 + Q_2 + \tau V Z_2 V^T,
\]
\[
\Pi_3 = [P W^T \sigma A^T Z_1],
\]
\[
\Pi_4 = \text{diag}\{-P_1, -\epsilon_1 I\},
\]
\[
\Pi_5 = -QB - BQ + M S_2 M + \tau B^T Z_2 B,
\]
\[
\Pi_6 = -S_2 + \tau X_2 - R_2 M^{-1} - M^{-1} R_2^T + P_1 + P_2 + \sigma W Z_1 W^T,
\]
\[
\Pi_7 = [Q V^T \tau B^T Z_2],
\]
\[
\Pi_8 = \text{diag}\{-Q_1, -\epsilon_2 I\}.
\]

Proof: Consider the following Lyapunov-Krasovskii functional

\[
V = V_1 + V_2 + V_3 + V_4 + V_5 + V_6 + V_7 + V_8
\]

where

\[
V_1 = x^T(t) P x(t), \quad V_2 = y^T(t) Q y(t),
\]
\[
V_3 = \int_{t-\sigma}^{t} x^T(s) M S_1 M x(s) ds, \quad V_4 = \int_{t-\tau}^{t} y^T(s) M S_2 M y(s) ds,
\]
\[
V_5 = 2 \sum_{i=1}^{n} d_i \int_{0}^{x_i(t)} f_i(s) ds, \quad V_6 = 2 \sum_{i=1}^{n} c_i \int_{0}^{y_i(t)} f_i(s) ds,
\]
\[
V_7 = \int_{-\sigma}^{0} \int_{t+\theta}^{t} \dot{x}^T(s) Z_1 \dot{x}(s) ds d\theta, \quad V_8 = \int_{-\tau}^{0} \int_{t+\theta}^{t} \dot{y}^T(s) Z_2 \dot{y}(s) ds d\theta.
\]

The time derivative of \(V_i\) along the trajectory of system (3) is

\[
\dot{V}_1 = 2 x^T(t) P (-A x(t) + W^T f(y(t - \tau)))
\]
\[
\dot{V}_2 = 2 y^T(t) Q(-B y(t) + V^T f(x(t - \sigma))),
\]
\[
\dot{V}_3 = x^T(t) M S_1 M x(t) - x^T(t - \sigma) M S_1 M x(t - \sigma),
\]
\[
\dot{V}_4 = y^T(t) M S_2 M y(t) - y^T(t - \tau) M S_2 M y(t - \tau),
\]
\[
\dot{V}_5 = 2 \dot{x}^T(x(t)) D \dot{x}(t) = 2 \dot{f}^T(x(t)) D(-A x(t) + W^T f(y(t - \tau))),
\]
\[
\dot{V}_6 = 2 \dot{f}^T(y(t)) E \dot{y}(t) = 2 \dot{f}^T(y(t)) E(-B y(t) + V^T f(x(t - \sigma))),
\]
\[
\dot{V}_7 = \sigma \dot{x}^T(t) Z_1 \dot{x}(t) - \int_{t-\sigma}^{t} \dot{x}^T(s) Z_1 \dot{x}(s) ds,
\]
\[
\quad = \sigma (-A x(t) + W^T f(y(t - \tau)))^T Z_1 (-A x(t) + W^T f(y(t - \tau)))
\]
\[
\quad - \int_{t-\sigma}^{t} \dot{x}^T(s) Z_1 \dot{x}(s) ds,
\]
\[
\dot{V}_8 = \dot{y}^T(t) Z_2 \dot{y}(t).
\]
where and using Lemma 3 we can obtain the following relations:
\[
\begin{align*}
\dot{V}_6 &= \tau \dot{y}^T(t)Z_2\dot{y}(t) - \int_{t-\tau}^{t} \dot{y}^T(s)Z_2\dot{y}(s)ds, \\
&= \tau(-By(t) + V^Tf(x(t)))(-By(t) + V^Tf(x(t))) \\
&- \int_{t-\tau}^{t} \dot{y}^T(s)Z_2\dot{y}(s)ds.
\end{align*}
\]
(9)

By the Leibniz-Newton formula, the following equations satisfy
\[
\begin{align*}
2\dot{f}^T(x(t-\sigma))\left(x(t) - x(t-\sigma) - \int_{t-\sigma}^{t} \dot{x}(s)ds\right) &= 0, \\
2\dot{f}^T(y(t-\tau))\left(y(t) - y(t-\tau) - \int_{t-\tau}^{t} \dot{y}(s)ds\right) &= 0.
\end{align*}
\]
(10)

Applying Lemma 2 to two terms in equation (10) gives that
\[
\begin{align*}
-2\int_{t-\sigma}^{t} \dot{f}^T(x(t-\sigma))\dot{x}(s)ds &\leq \sigma \dot{f}^T(x(t-\sigma))X_1\dot{f}(x(t-\sigma)) \\
+2\dot{f}^T(x(t-\sigma))(R_1 - I)(x(t) - x(t-\sigma)) + \int_{t-\sigma}^{t} \dot{x}^T(s)Z_1\dot{x}(s)ds, \\
-2\int_{t-\tau}^{t} \dot{f}^T(y(t-\tau))\dot{y}(s)ds &\leq \tau \dot{f}^T(y(t-\tau))X_2\dot{f}(y(t-\tau)) \\
+2\dot{f}^T(y(t-\tau))(R_2 - I)(y(t) - y(t-\tau)) + \int_{t-\tau}^{t} \dot{y}^T(s)Z_2\dot{y}(s)ds,
\end{align*}
\]
(11)

where
\[
\begin{bmatrix}
X_1 & R_1 \\
* & Z_1
\end{bmatrix} \succeq 0, \quad \begin{bmatrix}
X_2 & R_2 \\
* & Z_2
\end{bmatrix} \succeq 0.
\]
(12)

Here note that
\[
\begin{align*}
-x^T(t-\sigma)\overline{M}S_1\overline{M}x(t-\sigma) &\leq -\dot{f}^T(x(t-\sigma))S_1\dot{f}(x(t-\sigma)), \\
y^T(t-\tau)MS_2\overline{M}y(t-\tau) &\leq -\dot{f}^T(y(t-\tau))S_2\dot{f}(y(t-\tau)), \\
-2\dot{f}(x(t))DAx(t) &\leq -2\dot{f}(x(t))D\overline{M}^{-1}f(x(t)), \\
-2\dot{f}(y(t))EBy(t) &\leq -2\dot{f}(y(t))E\overline{M}^{-1}f(y(t)), \\
-2\dot{f}(x(t-\sigma))R_1x(t-\sigma) &\leq -2\dot{f}(x(t-\sigma))R_1\overline{M}^{-1}\dot{f}(x(t-\sigma)), \\
-2\dot{f}(y(t-\tau))R_2y(t-\tau) &\leq -2\dot{f}(y(t-\tau))R_2\overline{M}^{-1}\dot{f}(y(t-\tau)).
\end{align*}
\]
(13)

and using Lemma 3 we can obtain the following relations:
\[
\begin{align*}
2x^T(t)PW^Tf(y(t-\tau)) &\leq \dot{f}^T(y(t-\tau))P_1f(y(t-\tau)) + x^T(t)PW^TP_1^{-1}WPx(t), \\
2y^T(t)QV^T\dot{f}(x(t-\sigma)) &\leq \dot{f}^T(x(t-\sigma))Q_1\dot{f}(x(t-\sigma)) + y^T(t)QV^TQ_1^{-1}VQy(t),
\end{align*}
\]
\[2f^T(x(t))DWf(y(t - \tau)) \leq \bar{f}^T(x(t))DWP_2^{-1}WD\bar{f}(x(t)) + f^T(y(t - \tau))P_2f(y(t - \tau)),\]

\[2f^T(y(t))EVf(x(t) - \sigma) \leq \bar{f}^T(y(t))EVQ_2^{-1}VEf(y(t)) + \bar{f}^T(x(t) - \sigma)Q_2\bar{f}(x(t) - \sigma),\]

\[-2\sigma x^T(t)A^TZ_1W^Tf(y(t - \tau)) \leq \epsilon_1^{-1}\sigma^2 x^T(t)A^TZ_1Z_1Ax(t)
+ \epsilon_1f^T(y(t - \tau))WW^Tf(y(t - \tau)),\]

\[-2\tau y^T(t)B^TZ_2V^T\bar{f}(x(t) - \sigma) \leq \epsilon_2^{-1}\tau^2 y^T(t)B^TZ_2Z_2By(t)
+ \epsilon_2\bar{f}^T(x(t) - \sigma)VV^T\bar{f}(x(t) - \sigma).\] (14)

Substituting equations (11), (13) and (14) into equation (9) gives that

\[\dot{V} \leq z_1^T(t) \begin{bmatrix} N_1 & 0 & R_1^T \\ * & N_2 & 0 \\ * & * & N_3 \end{bmatrix} z_1(t) + z_2^T(t) \begin{bmatrix} N_4 & 0 & R_2^T \\ * & N_5 & 0 \\ * & * & N_6 \end{bmatrix} z_2(t)\]

\[\equiv z_1^T(t)\Omega_1 z_1(t) + z_2^T(t)\Omega_2 z_2(t)\] (15)

where

\[z_1(t) = [x^T(t)f^T(x(t))f^T(x(t) - \sigma)]^T,\]

\[z_2(t) = [y^T(t)f^T(y(t))f^T(y(t) - \tau)]^T,\]

\[N_1 = -P - AP + M^2 + PW^TP_1^{-1}WP + \sigma A^TZ_1A + \epsilon_1^{-1}\sigma^2 A^TZ_1Z_1A,\]

\[N_2 = -2DA\bar{M}^{-1} + DW^TP_2^{-1}WD,\]

\[N_3 = -S_1 + \sigma X_1 - R_1\bar{M}^{-1} - \bar{M}^{-1}R_1^T + Q_1 + Q_2 + \tau VZ_2V^T + \epsilon_2VV^T,\]

\[N_4 = -Q_1B - BQ + MS_2M + QV^TQ_1^{-1}VQ + \tau B^TZ_2B + \epsilon_2^{-1}\tau^2 B^TZ_2Z_2B,\]

\[N_5 = -2EBM^{-1} + EV^TQ_2^{-1}VE,\]

\[N_6 = -S_2 + \tau X_2 - R_2M^{-1} - M^{-1}R_2^T + P_1 + P_2 + \sigma WZ_1W^T + \epsilon_1WW^T.\]

From equation (15), if \(\Omega_1 < 0\) and \(\Omega_2 < 0\), then there exist positive scalars \(\delta_1\) and \(\delta_2\) such that \(\dot{V} \leq -\delta_1\|x(t)\|^2 - \delta_2\|y(t)\|^2\). Then, using Fact 1, the inequalities \(\Omega_1 < 0\) and \(\Omega_2 < 0\) are equivalent to (5) and (6) respectively. This completes our proof.

Remark 5: The criterion given in Theorem 4 is delay-dependent. It is well known that the delay-dependent criteria are generally less conservative than delay-independent criteria when the delay is small. The LMI solutions of Theorem 4 can be obtained by solving the eigenvalue problem with respect to solution variables, which is a convex optimisation problem. In this paper, we utilise Matlab’s Robust Control Toolbox (Gahinet et al., 1995) which implements interior-point algorithm. This algorithm is significantly faster than classical convex optimisation algorithms (Boyd et al., 1994).
Remark 6: By iteratively solving the LMIs given in Theorem 4 with respect to \( \tau \) and \( \sigma \), one can find the maximum upper bounds of time delay \( \tau \) and \( \sigma \) for guaranteeing asymptotic stability of system (3).

Example 7: Consider the following BAM neural networks

\[
\dot{x}_i(t) = -a_i x_i(t) + \sum_{j=1}^{2} w_{ji} f_j(y_j(t - \sigma)),
\]

\[
\dot{y}_j(t) = -b_j y_j(t) + \sum_{i=1}^{2} v_{ij} f_i(x_i(t - \sigma)), \quad i = 1, 2, \quad j = 1, 2.
\]

To take \( f_i(x) = \frac{1}{2}(|x_i + 1| - |x_i - 1|) \) and \( f_j(y) = \frac{1}{2}(|y_j + 1| - |y_j - 1|) \), then we have \( M_i = M_j = 1 \) for all \( i \) and \( j \), i.e., \( M = M = I \). Let

\[
A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix},
\]

\[
W = \begin{bmatrix} 1 & -0.4 \\ -0.4 & 1 \end{bmatrix}, \quad V = \begin{bmatrix} 0.65 & 1 \\ 1 & 0.65 \end{bmatrix}
\]

By applying Theorem 4 to the system (16), one can see that the LMIs given in Theorem 4 are feasible for any \( \sigma \). This implies that the system (16) is asymptotically stable for any delay \( \sigma > 0 \).

4 Concluding remarks

The global asymptotic stability of BAM neural networks with fixed time delay has been investigated. By using the Lyapunov theory and matrix inequality framework, a new delay-dependent stability criterion expressed by four LMIs is presented. To show the effectiveness of the proposed criterion, a numerical example is given.

References


