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STABILITY ANALYSIS OF NEURAL NETWORK INVOLVING TIME V DELAY: LMI APPROACH

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Abstract:

This paper is concern about the stability analysis of Hopfield neural network involving time varying delay for the discrete case. By constructing novel Lypunov Krovskii functional, we prove the stability results for the neural network with time varying delay. From the Proposed model, we derive linear matrix inequality. The sufficient results for a stability conditions are establish using from the employed Lypunov function and Linear Matrix Inequality. The Proposed system consists of the time delay dependent condition. Here we prove that the system gives the less conservative. The numerical results are provided to prove the theoretical result using MATLAB.

Key Words: Neural Network, Asymptotically Stable, Linear Matrix Inequality, Lyapunov Function & Delay Dependent

1. Introduction:

Neural networks (NNs) are widely studied, because of their immense potentials of application prospective in a variety of areas, such as signal processing, pattern recognition, static image processing, associative memory, and combinatorial optimization. In practice, time delay is frequently encountered in NNs. Due to the finite speed of information processing, the existence of time delays frequently causes oscillation, divergence, or instability in NNs. In recent years, the stability problem of delayed neural networks has become a topic of great theoretic and practical importance [1–14]. This issue has gained increasing interest in applications to signal and image processing, artificial intelligence, and so on.

In many physical and biological phenomena, the rate of variation in the system state depends on past states. This characteristic is called a delay or a time delay, and a system with a time delay is called a time-delay system. Time delay phenomena were first discovered in biological systems and were later found in many engineering systems, such as mechanical transmissions, fluid transmissions, metallurgical processes, and networked control systems. They are often a source of instability and poor control performance. Time-delay dependent systems have attracted the attention of many researchers [1, 5, 8, 12] because of their importance and widespread occurrence. Basic theories describing such systems were established in the 1950s and 1960s; they covered topics such as the existence and uniqueness of solutions to dynamic equations, stability theory for trivial solutions, etc. Much attention has also been considered to all kinds of time-delay system, because time delays are exist in a wide variety of practical systems, such as chemical processes, nuclear reactors and biological systems, and lead to the instability and poor performance of systems. Moreover, the stability problem of neural network systems with time delay has been widely investigated. For example, the stability of neural network systems with time delay has been considered in [2, 3, 4, 6, 9-12, 14], where some stability criteria have been proposed for testing whether the network systems are stable in terms of linear matrix inequality (LMI) approach. However, the conditions proposed in [8] are delay-independent and thus appear to be conservative, especially when the time delay is comparatively small. It should be pointed out that all of the above mentioned results on neural network time-delay systems are concerned with continuous-time systems. In terms of LMI method, the delay-dependent stability problem for discrete-time singular systems with time delay has been discussed in [1, 2, 5, 12, 13]. For example, based on the restricted system equivalent transformation, the considered discrete-time neural network system with time-varying delays is transformed into a standard state-space system in [12], where a delay-dependent LMI condition has been proposed to ensure the systems to be admissible. In [4], without resorting to the decomposition and equivalent transformation of the considered systems, some new delay-dependent criteria have been established for the discrete-time singular systems to be regular, causal, and stable based on LMI approach. Discrete-time systems with state delay have strong background in engineering applications, among which network based control has been well recognized to be a typical example. If the delay is constant, one can transform a delayed system into a delay-free one by using state augmentation techniques. In this way, stability of such systems can be readily tested by employing classical results on stability analysis.

In this paper, we revisit the problem of stability analysis for discrete time systems with a time-varying delay in the state, which has been investigated in [12]. By defining new Lyapunov functions, and by making use of novel techniques to achieve delay dependence, several new results are presented for the asymptotic stability. Here the given example illustrates the advantage of the developed results. This paper is organized as follows, in section 2, we deal with problem formulation, section 3, presents some general preliminaries which is suitable to main results. In section 4, we construct a main result of the proposed model. Here we have framed the Lyapunov and linear matrix inequality. Based on these assumption, we arrived at the system is globally exponentially stable. Finally last section deals with numerical results, which gives the desired output for the proposed model.

Notations:

Throughout this paper $\mathbb{R}^n$ and $\mathbb{R}^{n*m}$ denotes the n dimension Euclidean space and set of all $n \times n$ real matrices, respectively. A real symmetric matrix P>0 denotes P being a positive definite matrix. I is used to denote an identity matrix with proper dimensions. The symmetric terms in asymmetric matrix are denoted by *.

2. Mathematical Formulation of the System:

The dynamic behavior of a discrete Hopfield neural network can be described as follows:

$$y(k+1) = Ay(k) + Bf\big(y(k)\big) + Cf(y(k-h_k) + J \qquad (1)$$

$$y(k) = \theta(k), \qquad -h \le k \le 0$$

Where $y(.) = [y_1(.), y_2(.), \dots, y_n(.)]^T \in \mathbb{R}^n$ is the neuron state vector, the activation neuron is given by $fy(.) = [fy_1(.), fy_2(.), \dots, fy_n(.)]^T \in \mathbb{R}^n, J = [j_1, j_2, \dots, j_n] \in \mathbb{R}^n$ is a constant input vector, A$= diag\{a_1, a_2, \dots, a_n\}$ is a positive diagonal matrix with $|a_i| < 1$ (i=1,2,…,n), and B and C are the connection weight matrix and the delayed connection weight matrix respectively. The time delay h_k is the time varying delay and satisfies, $0 < h_m \le h_k \le h_M$. where h_m and h_M are positive integers.

Assumption 1:

For [i=1,2,…,n], the given activation function $f(y(k))$ are continuous and bounded. For any $, y \in R,\ x \ne y$,

$$l_i \le \frac{f_i(x) - f_i(y)}{x - y} \le m_i \quad, i = 1,2, \dots, n \qquad (2)$$

Where, l_i and m_i are constants.

Remark 1:

The neural networks of the system (1) are the static neural networks. Assume that $y^* = [y_1^*, y_2^*, \dots, y_n^*]^T$ is an equilibrium point of system (1), by choosing the coordinate transformation, $z_i(k) = y_i(k) - y_i^*$.

Now System (1) is changed into the following error systems.

$$z(k+1) = Az(k) + Bg(z(k)) + C(g(z(k - h_k))) \qquad (3)$$

$$y(k) = \varphi(k) \quad, -h \le k \le 0$$

where $z(.) = [z_1(.), z_2(.), \dots, z_n(.)]^T \in \mathbb{R}^n$ is the neuron state vector of the transformed system, by $gy(.) = [g_1 z_1(.), g_2 z_2(.), \dots, g_n z_n(.)]^T \in \mathbb{R}^n$ and $gz(.) = [gz_1(.), gz_2(.), \dots, gz_n(.)]^T = f(z(.) + y^*) - f(y^*) \in \mathbb{R}^n$. Then the function $g_i(.), i = 1,2, \dots, n$ satisfies the following condition,

$$l_i \le \frac{g_i(z_i(k))}{z_i(k)} \le m_i \qquad (4)$$

$g_i(0) = 0, for\ all\ z_i(k) \ne 0\ i = 1,2, \dots, n$ Where, l_i and m_i are constants. $\varphi(k) = \theta(k) - y^*$ is the initial condition.

Throughout this work, the discrete Jensen inequality will be used, so it is listed as the following lemmas.

3. Preliminaries:

Lemma 3.1: For any constant matrix $M \in \mathbb{R}^n$, $M = M^T > 0$, integeres $l_2 \ge l_1$, vector function $W: [l_1, l_1 + 1, \dots, l_2] \to R^n$ such that the sums in the following are well defined then,

$$-(l_2 - l_1 + 1) \sum_{i=l_1}^{l_2} w^T(i) M w(i) \le \left(\sum_{i=l_1}^{l_2} w(i)\right)^T M \left(\sum_{i=l_1}^{l_2} w(i)\right) \qquad (5)$$

Lemma 3.2: Shur Complements: The following LMI

$$\begin{bmatrix} Q(x) & S(x) \\ * & R(x) \end{bmatrix} \le 0 \qquad (6)$$

Where $Q(x) = Q^T(x),\ R(x) = R^T(x)$ and *S(x)* depends on *x*, is equivalent to

$$R(x) < 0,\ \ Q(x) - S(x) R(x)^{-1} S^T(x) < 0$$

$$Q(x) < 0,\ \ R(x) - S(x) Q(x)^{-1} S^T(x) < 0$$

Lemma 3.3: For any real vector *a,b* and any matrix $Q > 0$ with the appropriate dimensions, we have

$$2a^T b \le a^T X a + b^T X^{-1} b \qquad (7)$$

Remark 1: The class of systems (3) represents a nominally nonlinear model emerges in many areas dealing with the applications of functional difference equation or delay difference equation.

4. Main Results:

In this section, we will discuss some new asymptotical stability criteria for the considered neural networks.

Theorem 4.1: For given diagonal matrix $L = diag\{l_1, l_2, \dots, l_n\}$ and scalars $h_m \ge 0$ and $h_M \ge 0$, the system (3) and (4) is globally asymptotically stable, if there exist matrices $P = \begin{bmatrix} P_1 & P_2 \\ * & P_3 \end{bmatrix} > 0$, $Q_i = Q_i^T \ge 0$, (i=1,2,…,n), $U_j = U_j^T > 0$, j=1,2,…,n are to be determined, and $\lambda_j = diag\{\lambda_1, \lambda_2, \dots, \lambda_n\} \ge 0$, $T_j = diag\{t_1, t_2, \dots, t_n\} \ge 0$, such that the following inequality hold:

$$\Phi = \begin{bmatrix} \varphi_{11} & A^T P_2 & \frac{1}{h_m} U_1 & 0 & \varphi_{15} & \varphi_{16} & \varphi_{17} \\ * & \varphi_{22} & \varphi_{23} & \varphi_{24} & 0 & P_2^T B & \varphi_{27} \\ * & * & \varphi_{33} & 0 & 0 & 0 & 0 \\ * & * & * & \varphi_{44} & 0 & 0 & 0 \\ * & * & * & * & P_3 & P_2^T B & P_2^T C \\ * & * & * & * & * & \varphi_{66} & \varphi_{67} \\ * & * & * & * & * & * & \varphi_{77} \end{bmatrix} < 0 \qquad (8)$$

Where,

$$\varphi_{11} = A^T P_1 A + A^T P_2 + P_2^T A + P_1 + Q_2 + Q_3 + (h_M - h_m + 1) Q_1 + (A - I)^T U (A - I) - \frac{1}{h_m} U_1 - 2r\lambda_1 + 2\varepsilon T_1$$

$$\varphi_{15} = A^T P_2 + P_2$$

$\varphi_{16} = A^T P_1 B + P_2^T C + (A-I)^T UB + \lambda_1 + (r+\varepsilon)T_1$
$\varphi_{17} = A^T P_1 C + P_2^T C + (A-I)^T UC$
$\varphi_{22} = Q_1 - \frac{1}{h_M - h_m}(U_1 + U_2) - 2r(\lambda_2 + \varepsilon T_2)$
$\varphi_{23} = \frac{1}{h_M - h_m}(U_1 + U_2)$
$\varphi_{24} = \frac{1}{h_M - h_m}(U_1 + U_2)$
$\varphi_{27} = \lambda_2 + [r+\varepsilon]T_2$
$\varphi_{33} = -Q_2 - \frac{1}{h_M}U_1 - \frac{1}{h_M - h_m}(U_1 + U_2)$
$\varphi_{44} = -Q_3 - \frac{1}{h_M - h_m}(U_1 + U_2)$
$\varphi_{66} = B^T P_1 B + B^T UB - 2T_1$
$\varphi_{67} = B^T P_1 C + B^T U_2 C$
$\varphi_{77} = C^T P_1 C + C^T UC - 2T^2$
$U = h_M U_1 + (h_M - h_m)U_2$

Proof: In this theorem, new delay dependent stability criteria are proposed for system (3) and (4) with time varying delay satisfying $0 < h_m \le h_k \le h_M$. we denote, $\varepsilon = diag\{\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n\}$ and $r = diag\{\gamma_1, \gamma_2, \dots, \gamma_n\}$.
Firstly, we consider, the following Lypunov Krosovskii functions,

$$V(k) = \sum_{i=1}^{7} V_i(k) \qquad (9)$$

Where,

$$V_1(k) = \chi(k)^T P \chi(k)$$
$$V_2(k) = \sum_{i=k-h_k}^{k-1} z(i)^T Q_1 z(i)$$
$$V_3(k) = \sum_{i=k-h_m}^{k-1} z(i)^T Q_2 z(i)$$
$$V_4(k) = \sum_{i=k-h_M}^{k-1} z(i)^T Q_3 z(i)$$
$$V_5(k) = \sum_{j=-h_M+1}^{-h_m} \sum_{i=k+j}^{k-1} z(i)^T Q_1 z(i)$$
$$V_6(k) = \sum_{i=-h_M}^{-1} \sum_{j=k+i}^{k-1} \eta(i)^T U_1 \eta(i)$$
$$V_7(k) = \sum_{i=-h_M}^{-1} \sum_{j=k+i}^{k-1} \eta(i)^T U_1 \eta(i)$$

Where, $\eta(k) = z(k+1) - z(k)$, with $\chi(k)^T = \begin{bmatrix} z(k)^T & \sum_{i=k-h_k}^{k-1} z(i)^T \end{bmatrix}$, $P = \begin{bmatrix} P_1 & P_2 \\ * & P_3 \end{bmatrix} > 0, Q_i > 0, i = (1,2,3), U_i > 0, i = (1,2)$.

Take derivative of equation, $\Delta V(k) = V(k+1) - V(k)$

$\Delta V_1(k) = \chi(k+1)^T P \chi(k+1) - \chi(k)^T P \chi(k)$
$= \begin{bmatrix} z(k+1)^T & \sum_{i=k+1-h_k}^{k} z(i)^T \end{bmatrix} \begin{bmatrix} P_1 & P_2 \\ * & P_3 \end{bmatrix} \begin{bmatrix} z(k+1) & \sum_{i=k+1-h_k}^{k} z(i) \end{bmatrix}^T - \begin{bmatrix} z(k)^T & \sum_{i=k-h_k}^{k-1} z(i)^T \end{bmatrix} \begin{bmatrix} P_1 & P_2 \\ * & P_3 \end{bmatrix} \begin{bmatrix} z(k) & \sum_{i=k-h_k}^{k-1} z(i) \end{bmatrix}^T$

$\Delta V_2(k) = V_2(k+1) - V_2(k)$
$\le z^T(k) Q_1 z(k) - z^T(k-h_k) Q_1 z(k-h_k) + \sum_{i=k-d_M+1}^{k-d_m} z(i)^T Q_1 z(i)$

$\Delta V_3(k+1) = V_3(k+1) - V_3(k)$
$= z^T(k) Q_2 z(k) - z^T(k-h_m) Q_2 z(k-h_m)$

$\Delta V_4(k+1) = V_4(k+1) - V_4(k)$
$= z^T(k) Q_3 z(k) - z^T(k-h_M) Q_3 z(k-h_M)$

$\Delta V_5(k) = V_5(k+1) - V_5(k)$
$= (h_M - h_m) z^T(k) Q_1 z(k) - \sum_{i=k-h_M}^{k-h_m} z^T(i) Q_1 z(i)$

$\Delta V_6(k) = V_6(k+1) - V_6(k)$
$= h_M \eta^T(k) U_1 \eta(k) - \sum_{j=k-h_m}^{k-1} \eta^T(j) U_1 \eta(j) - \sum_{j=k-h_k}^{k-h_m-1} \eta^T(j) U_1 \eta(j) - \sum_{j=k-h_M}^{k-h_k-1} \eta^T(j) U_1 \eta(j)$

$\Delta V_7(k) = V_7(k+1) - V_7(k)$
$= (h_M - h_m) \eta^T(k) U_2 \eta(k) - \sum_{j=k-h_k}^{k-h_m-1} \eta^T(j) U_2 \eta(j) - \sum_{j=k-h_M}^{k-h_k-1} \eta^T(j) U_2 \eta(j)$

From (4), for any diagonal $T_j = diag\{t_{1j}, t_{2j}, \dots, t_{nj}\} \ge 0, (j = 1,2)$, there exists

$$0 \le -2\left(g(z(k))\right) - \varepsilon z(k)^T T_1 \left(g(z(k))\right) - r z(k) \qquad (10)$$
$$0 \le -2\left(g(z(k-h_k))\right) - \varepsilon z(k-h_k)^T T_2 \left(g(z(k-h_k))\right) - r z(k-h_k) \qquad (11)$$

Similarly, for any $\lambda_j = diag\{\lambda_{1j}, \lambda_{2j}, \dots, \lambda_{nj}\} \ge 0, \quad (j = 1,2)$, it gives

$$0 \le 2\left(g^T(z(k))\right) \lambda_1 z(k) - 2z(k)^T r \lambda_1 z(k) \qquad (12)$$
$$0 \le 2\left(g^T(z(k-h_k))\right) \lambda_2 z(k-h_k) - 2z(k-h_k)^T r \lambda_2 z(k-h_k) \qquad (13)$$

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$$\Delta V(k) = \sum_{i=1}^{7} \Delta V_i(k) \quad (14)$$

Adding the terms on the left side of the equation (10) to (14), we get,

$$\Delta V(k) \leq \mu^T(k)\Phi\mu(k)$$

Where,

$$\mu(k) = \begin{bmatrix} z^T(k) & z^T(k-h_k) & z^T(k-h_m) & z^T(k-h_M) & \sum_{i=k-h_k}^{k-1} z(i)^T & g(z(k))^T & g(z(k-h_k))^T \end{bmatrix}$$

And the value of Φ is given in equation (6), so if $\Phi < 0$ then we have $\Delta V(k) < 0$.

This completes the proof

Remark 2: Here we use the new stability condition which is obtained by using discrete Jensen inequality. Using the same condition we also establish the exponential stability for a system (3) with the initial condition. It s very important the given system must satisfied the bounded condition $0 < h_m \leq h_k \leq h_M$.

Remark 3: In this paper, a novel Lyapunov function is applied, which involves the information of $\sum_{i=k-h_k}^{k-1} z(i)$. Here the approach will produce less convertism of the existing results in static neural network.

Remark 4: The sufficient condition in Theorem 4.1 can prove the global asymptotic stability of neural network of (3), and the stability condition is expressed in the form of LMI which can be easily checked using MATLAB.

If $h_k$is unknown or h_m, h_M not existing, put $Q_i = 0,\ i = (1,2,3)$ in the above theorem, then the system (3) lead to an independent stability.

Corollary 4.2: For a given diagonal matrix $L = diag\{l_1, l_2, \ldots, l_n\}$ and scalar $h_k \geq 0$. If the System (3) along with (4) is globally asymptotically stable, then there exists a matrix$P = \begin{bmatrix} P_1 & P_2 \\ * & P_3 \end{bmatrix} > 0, Q_2 > 0,\ U_i > 0,\ \ (i = 1,2)$ for the appropriate dimension such that the following holds,

$$\Phi = \begin{bmatrix} \varphi_{11} & A^T P_2 & \frac{1}{h_m} U_1 & 0 & \varphi_{15} & \varphi_{16} & \varphi_{17} \\ * & \varphi_{22} & \varphi_{23} & \varphi_{24} & 0 & P_2^T B & \varphi_{27} \\ * & * & \varphi_{33} & 0 & 0 & 0 & 0 \\ * & * & * & \varphi_{44} & 0 & 0 & 0 \\ * & * & * & * & P_3 & P_2^T B & P_2^T C \\ * & * & * & * & * & \varphi_{66} & \varphi_{67} \\ * & * & * & * & * & * & \varphi_{77} \end{bmatrix} < 0 \quad (15)$$

The parameter values are given in the above theorem (4.1), substitute Q_1 and $Q_3$are equal to zero then the system will lead to the above inequality (15).

Remark 5: It is very necessary to assume that$h_m \neq h_M$. Because, if we assume that $h_m = h_M$then some of the values in the parameter of LMI (6) such as φ_{23} and φ_{24}tends to infinite, so the system may be unstable. Also $h_m < h_M$.

From this condition it is very important that the given system (3) must satisfies the delay condition, $0 < h_m \leq h_k \leq h_M$.

5. Numerical Example:

Example 1: Consider the delayed discrete time with Hopfield neural network in system (3), the parameters are given by,

$$A = \begin{bmatrix} 0.8 & 0 \\ 0 & 0.9 \end{bmatrix}, B = \begin{bmatrix} 0.001 & 0 \\ 0 & 0.005 \end{bmatrix}, C = \begin{bmatrix} -0.1 & 0.01 \\ -0.2 & -0.1 \end{bmatrix}$$

The activation function satisfy the assumption 1 with

$$r = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, \varepsilon = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

For various h_m, the upper bounds of delay h_k, h_M are obtained by different methods, which are given below.

Methods	$d_m = 2$	$d_m = 5$	$d_m = 11$	$d_m = 15$
Theorem 1 [5]	11	11	15	17
Theorem 1 [1]	11	12	16	19
Theorem 1 [12]	11	13	17	20
Theorem 1	11	14	17	21

From which it can be seen that the delay dependent stability criteria proposed in this systems are less conservative.

Numerical Simulation: Figure 1Demonstrate that the given system of discrete Hopfield neural network is asymptotically stable. For the different state value and the above proved example the given system is reached to zero, this shows that (3) is asymptotically for time varying delays.

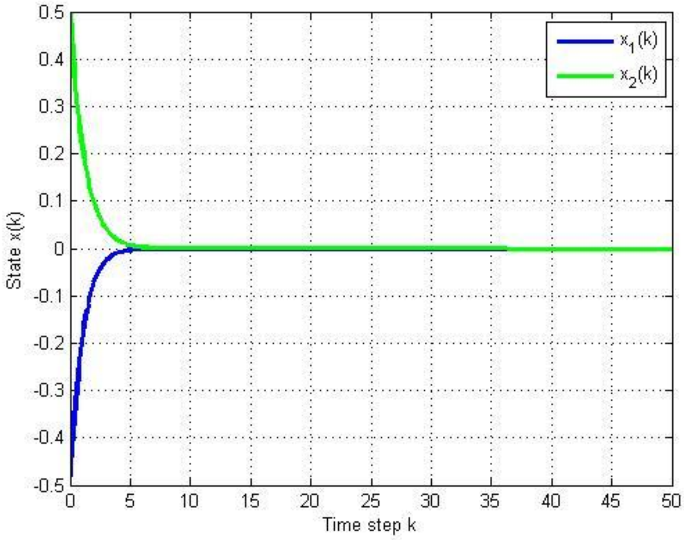

Figure 1: The state curve of a Hopfield neural network.

6. Conclusion:

In this paper, the delay dependent stability problem of discrete Hopfield neural network with time varying delay has been investigated. By employing Lypunov krosovski functions and linear matrix inequality, the new delay dependent conditions are obtained. The necessary conditions of delay bound and the discrete Linear matrix inequality criterion is derived in terms of linear matrix inequality. The newly obtained results are less conservative. The existent results are proved through MATLAB. As a further work, the delay dependent method will be extending to complex valued neural network with bounded time varying delay.

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