



# Synchronization of non-identical chaotic delayed fuzzy cellular neural networks based on sliding mode control <sup>☆</sup>

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## ARTICLE INFO

### Article history:

Received 13 December 2010  
Received in revised form 16 April 2011  
Accepted 10 May 2011  
Available online 18 May 2011

### Keywords:

Synchronization  
Fuzzy cellular neural networks  
Lyapunov–Krasovskii functional  
Sliding mode control

## ABSTRACT

–In this paper, we investigate the synchronization problems of chaotic fuzzy cellular neural networks with time-varying delays. To overcome the difficulty that complete synchronization between non-identical chaotic neural networks cannot be achieved only by utilizing output feedback control, we use a sliding mode control approach to study the synchronization of non-identical chaotic fuzzy cellular neural networks with time-varying delays, where the parameters and activation functions are mismatched. This research demonstrates the effectiveness of application in secure communication. Numerical simulations are carried out to illustrate the main results.

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## 1. Introduction

The human brain is made up of a large number of cells called neurons and their interconnections. An artificial neural network is an information processing system that has certain characteristics in common with biological neural networks. Since the pioneering work on cellular neural networks (CNNs) in [6,7], the investigation of the dynamics of neural networks has been the subject of much recent activity due to their promising potential applications such as signal processing, pattern recognition, optimization and associative memories. Some important results have been reported (see, for example [2,4,20,21] and the references therein).

However, in mathematical modeling of real world problems, we encounter two inconveniences, namely, the complexity and the uncertainty or vagueness. In order to take vagueness into consideration, fuzzy theory is considered as a suitable setting. Based on traditional CNN, Yang and Yang proposed the fuzzy CNN (FCNN) [24,25], which integrates fuzzy logic into the structure of traditional CNN and maintains local connectedness among cells. Unlike previous CNN structures, FCNN have fuzzy logic between its template input and/or output besides the sum of product operation. Some results on stability have been derived for the FCNN models without time delays (see, [26]). It is well-known that there exist time delays in the information processing of neurons due to various reasons. For example, time delays can be caused by the finite switching speed of amplifier circuits in neural networks or deliberately introduced to achieve tasks of dealing with motion-related problems, such as moving image processing. Time delays in the fuzzy cellular neural networks make the dynamic behaviors become more complicated, and may destabilize the stable equilibria and admit periodic oscillation, bifurcation and chaos (see e.g., [12,23,28] and the references therein). Therefore, considerable attention has been made on the study of delayed fuzzy cellular neural networks and a large body of work has been reported in the literature (see, e.g., [11,16,18] and the references therein).

<sup>☆</sup> This work was supported by the National Natural Science Foundation of China (Nos. 10671209, 11071254) and the Scientific Research Foundation for the Returned Overseas Chinese Scholars, State Education Ministry.

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Synchronization problems of chaotic fuzzy delayed cellular neural networks have been intensively investigated in the last decade due to its potential applications in various technological fields, including chaos generators design, secure communications, chemical reactions, biological neural networks, information processing, etc. (see [8,9,19,23] and the references therein). However, most researches focused on synchronizing two identical chaotic delayed fuzzy cellular neural networks with different initial conditions. But in practical situations, due to the mismatched parameters and activation functions which is unavoidable in real implementation, the drive system and response system are not identical and the resulting synchronization is not exact and complex. Therefore, it is important and challenging to study the synchronization of non-identical chaotic fuzzy cellular neural networks with delays. Motivated by the above discussions, the aim of this paper is to discuss the complete synchronization for a class of non-identical chaotic fuzzy cellular neural networks with time-varying delays based on sliding mode control. We also apply the proposed synchronization scheme towards the chaotic secure communication.

The organization of this paper is as follows: in the next section, model description and preliminary results are presented; in Section 3, a sliding mode control scheme is proposed to ensure the complete synchronization of non-identical chaotic fuzzy cellular neural networks with time-varying delays; numerical simulations will be given in Section 4 to demonstrate the effectiveness of our results; in Section 5, the proposed sliding mode control scheme is applied to secure communication. Finally, conclusions are drawn in Section 6.

### 2. Modeling and preliminary

Throughout this paper,  $R^n$  and  $R^{n \times m}$  denote the  $n$  dimensional Euclidean space and the set of all  $n \times m$  real matrices, respectively; the superscript “ $T$ ” denotes matrix transposition. For  $A, B \in R^{n \times n}$ ,  $A \leq B$  means that each pair of the corresponding elements of  $A$  and  $B$  satisfy the inequality “ $\leq$ ” (“ $>$ ”). Also, if  $A = (a_{ij})$ , then  $|A| = (|a_{ij}|)$ . And the symmetric terms in asymmetric matrix are denoted by  $*$ .

In this paper, we are concerned with the following fuzzy cellular neural networks with time-varying delays:

$$\begin{aligned} \dot{x}_i(t) = & -d_i x_i(t) + \sum_{j=1}^n a_{ij} f_j(x_j(t)) + \sum_{j=1}^n b_{ij} f_j(x_j(t - \tau(t))) + \bigwedge_{j=1}^n \alpha_{ij} f_j(x_j(t - \tau(t))) + \bigvee_{j=1}^n \beta_{ij} f_j(x_j(t - \tau(t))) + \sum_{j=1}^n c_{ij} \mu_j \\ & + \bigwedge_{j=1}^n T_{ij} \mu_j + \bigvee_{j=1}^n H_{ij} \mu_j + I_i, \end{aligned} \tag{2.1}$$

where  $i = 1, 2, \dots, n$ ,  $n$  is the number of neurons in the networks;  $x(t) = (x_1(t), x_2(t), \dots, x_n(t))^T$  is the state vector associated with the neurons;  $\alpha_{ij}$  and  $\beta_{ij}$  are elements of fuzzy feedback MIN template and fuzzy feedback MAX template, respectively;  $T_{ij}$  and  $H_{ij}$  are fuzzy feedforward MIN template and fuzzy feedforward MAX template, respectively;  $a_{ij}$  and  $b_{ij}$  are elements of feedback templates and  $c_{ij}$  is the feedforward template;  $\bigwedge$  and  $\bigvee$  denote the fuzzy AND and fuzzy OR operation, respectively;  $\mu_j$  and  $I_i$  denote input and bias of the  $i$ th neurons, respectively;  $\tau$  correspond to the transmission delay;  $f_j(\cdot)$  is the activation function of the  $j$ th neurons at time  $t$ .

In order to observe the synchronization behavior of system (2.1), we introduce another delayed fuzzy cellular neural network as follows:

$$\begin{aligned} \dot{y}_i(t) = & -\hat{d}_i y_i(t) + \sum_{j=1}^n \hat{a}_{ij} g_j(y_j(t)) + \sum_{j=1}^n \hat{b}_{ij} g_j(y_j(t - \tau(t))) + \bigwedge_{j=1}^n \hat{\alpha}_{ij} g_j(y_j(t - \tau(t))) + \bigvee_{j=1}^n \hat{\beta}_{ij} g_j(y_j(t - \tau(t))) + \sum_{j=1}^n c_{ij} \mu_j \\ & + \bigwedge_{j=1}^n T_{ij} \mu_j + \bigvee_{j=1}^n H_{ij} \mu_j + \zeta_i(t) + J_i, \end{aligned} \tag{2.2}$$

where  $i = 1, 2, \dots, n$ ;  $y_i(t)$  correspond to the states of the  $i$ th neural unit at time  $t$ ;  $\hat{\alpha}_{ij}$  and  $\hat{\beta}_{ij}$  are elements of fuzzy feedback MIN template and fuzzy feedback MAX template, respectively;  $\hat{a}_{ij}$  and  $\hat{b}_{ij}$  are elements of feedback template;  $J_i$  denotes bias of the  $i$ th neurons, respectively;  $g_j(\cdot)$  is the activation function of the  $j$ th neurons at time  $t$ ;  $\zeta(t) = (\zeta_1(t), \zeta_2(t), \dots, \zeta_n(t))^T$  is the appropriate control input that will be designed in order to obtain a certain control objective.

Define the error signal as  $e(t) = (e_1(t), e_2(t), \dots, e_n(t))^T = x(t) - y(t) = (x_1(t) - y_1(t), x_2(t) - y_2(t), \dots, x_n(t) - y_n(t))^T$  and subtracting (2.1) from (2.2) yields the error system as follows:

$$\begin{aligned} \dot{e}_i(t) = & -d_i e_i(t) - (d_i - \hat{d}_i) y_i(t) + \sum_{j=1}^n a_{ij} h_j(e_j(t)) - \sum_{j=1}^n \hat{a}_{ij} g_j(y_j(t)) + \sum_{j=1}^n a_{ij} f_j(y_j(t)) + \sum_{j=1}^n b_{ij} h_j(e_j(t - \tau(t))) - \sum_{j=1}^n \hat{b}_{ij} g_j(y_j(t - \tau(t))) \\ & + \sum_{j=1}^n b_{ij} f_j(y_j(t - \tau(t))) + \bigwedge_{j=1}^n \alpha_{ij} h_j^*(e_j(t - \tau(t))) - \bigwedge_{j=1}^n \hat{\alpha}_{ij} g_j(y_j(t - \tau(t))) + \bigwedge_{j=1}^n \alpha_{ij} f_j(y_j(t - \tau(t))) + \bigvee_{j=1}^n \beta_{ij} h_j^*(e_j(t - \tau(t))) \\ & - \bigvee_{j=1}^n \hat{\beta}_{ij} g_j(y_j(t - \tau(t))) + \bigvee_{j=1}^n \beta_{ij} f_j(y_j(t - \tau(t))) - \zeta(t) + I_i - J_i, \end{aligned} \tag{2.3}$$

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