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# A novel chaotic hetero-associative memory

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ABSTRACT

In this study, a novel hetero-associative memory with dynamic behavior is proposed. The proposed hetero-associative memory can store as twice as a regular hetero-associative memory using a new extension of sparse learning method. The new learning method gives the network ability of successive learning, therefore it can store new patterns even after learning phase. In other words, learning step and recall step are not separated in this method. We also add chaos searching in recall step in order to make the network be able to converge into the best possible solution among whole search space. Chaotic behavior helps the network jumps from local minimums. Simulation result shows higher storage capacity and also better recall performance in comparison with regular hetero-associative memory with the presence of noisy input data.



## 1. Introduction

One of the most interesting features of human brain is its ability in association of information. We associate human faces with names, we can also recognize people even if they get older. This primary function of the brain is called Associative Memory. This feature is useful in many different fields especially in data mining.

To implement associative memory some methods were introduced and the most interesting and efficient one is the Associative Memory Networks [1]. Associative memory networks are single layer nets that can store and recall patterns based on data content rather than data address. Associative memory stores pattern associations and each association is a pair of input/output vector ($s$, $t$). If $s$ vector and $t$ vector are the same, then the associative memory is called Auto-Associative Memory and if they are different vectors, then it is called Hetero-Associative Memory. Hetero-associative memories can store the association between two different types. For example, hetero-associative memories can store alphabet sounds that are related to their associated alphabet graphic patterns. Although associative memory can learn and store associated patterns successfully, its capacity is restricted by neuron size and the number of learning patterns.

To improve capacity storage of the associative memory some new learning methods are introduced which are more efficient rather than the conventional associative memory [1,2]. It says that studies have shown chaotic behavior of real neurons and it is considered that chaos plays an important role in information processing of human brain [3–5]. Consequently, chaos was noticed as a new solution to be used in associative memory. Several articles have been introduced based on chaotic theory which show improvement of associative memories performance especially in deal with noisy data.

There is also another kind of associative memories that use matrix operation instead of algebra called Lattice associative memory. Recently they have become more interesting as they can store more patterns than conventional hetero-associative [6]. Ritter et al. present morphological associative memories based on morphological neural networks which converge in one step, and also have unlimited storage capacity for perfect recall. It has been shown that morphological auto-associative memories can exhibit superior performance for noisy inputs and carefully chosen kernels [6]. In what follows, morphological bidirectional associative memories have been introduced by Ritter et al. [7], which have the ability to reconstruct input patterns using associated output as well as recalling outputs using input samples. Although associative morphological memories have excellent recall properties, they suffer from the sensitivity to specific noise models [8]. Raducanu et al. proposed a construction method to improve Morphological memory robustness to noise [9].

In this paper a novel hetero-associative memory with a new learning method and chaotic dynamic behavior of its neurons is proposed. A new weight structure is introduced to make the network robust to noise by employing chaotic behavior. There are two weight vectors, one for internal association of input patterns and the other one is proposed to keep input/output association. The first weight vector is trained based on Hebbian

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rule and the second input/output weight vector is adjusted based on input/output correlations due to an extension of sparse learning method which is called Less Correlation Less Effect (LCLE). The structure of weight vectors gives the network ability of successive learning, therefore, it can learn new data after training step and does not need to retrain all previous stored patterns. In the recall step, chaotic neurons and a chaos control method are proposed to help the network converge to the best possible associated input/output stored pattern. A series of computer simulation shows the effectiveness of the proposed method and significant improvements of the network capacity and noise resistance.

The rest of this paper is organized as follows. Related works are briefly represented in Section 2. Regular hetero-associative memory is briefly represented in Section 3. We report S-GCM model which has been applied for information processing in Section 4. In Section 5, topology of the proposed learning method and dynamics of neurons are described. Section 6 experimentally explains how the proposed method stores and recalls patterns and it also presents some numerical results of our implementation. Finally, some discussion and conclusions are given in Section 7.

## 2. Related works

In the last two decades, chaotic neural networks have drawn a lot of attention as a method of information processing. Aihara proposed a single neuron with chaotic dynamics by considering properties of biological neurons for the first time. He shows chaotic solutions of both single chaotic neuron and chaotic neural network composed of chaotic neurons. His network is noticed as a basic model of chaotic neural network and a lot of different chaotic neural networks have been proposed based on that [10]. Osana et al. introduced a chaotic bidirectional associative memory in order to enable one-to-many associations storage. In the proposed method, each training pair is memorized with its own contextual information and chaotic neurons are used in a part of the network corresponding to the contextual information [11]. Osana and Hagiwara proposed a chaotic neural network with the ability of successive learning. The proposed method can distinguish an unknown pattern from the stored known patterns and learn the unknown pattern successively [12]. Ju-Jang Lee designed a dynamic bidirectional associative memory with the ability of multiple memory access which is designed based on the dynamics of the chaotic neurons [13]. Ando et al. introduced a method based on a hetero-chaotic associative memory for successive learning and the multiwinners self-organizing neural network [14]. The proposed method improved storage capacity by internal pattern generation based on multiwinner competition [14]. Osana also introduced a chaotic hetero-associative memory with give-up function which is able to provide successive learning [15]. Wang et al. represented a network which exhibits rich dynamic behaviors) using sine map and chaotic neurons in a different way of coupling [16]. The proposed network can be controlled to any periodic orbits by applying parameter threshold which shows performance improvement [16].

Although chaotic neural network presents complex dynamics and can be used in information processing, states of chaotic neural network may wander around all the stored patterns and cannot be stabilized to one of the stored patterns [16]. A series of articles worked on this issue to find a way in order to control chaos in chaotic neural network. Bueno and Araujo introduced a control strategy through pining control method to make hetero-associative chaotic networks converge towards a desired non-accessible memory and last state of a trajectory [17]. Zheng and Tang proposed a method to control the parameters of S-GCM map [18]. In this model, both the value of system partial energy and its difference affect parameters. He et al. represent a novel chaos control scheme, a parameter modulated control method, for the chaotic neural networks which is applied particularly for associate memory. Authors suggest a scheme which provides a type of adaptive control method in which the refractory scaling parameter decreases by the addition of a delay feedback control signal to the network [19]. In addition, a dynamic depression control method imposed on the internal state of neurons was introduced by Xia et al in 2010. In this method, the decay parameters and the scaling parameters for the refractoriness were determined by the internal state of neurons. Moreover, chaos is controlled using dynamic depression in a self-adaptive manner and without any specific target [20]. Aihara et al. have proposed the chaotic neural network with threshold activated coupling, which provides a controlled network with dynamic behavior. The network converges to one of its stored patterns which has the smallest Hamming distance from the initial state of the network [21].

## 3. Regular hetero-associative memory

As it is mentioned in Section 2, a hetero-associative memory can store a set of pattern associations based on the correlation between input and output samples when they are not the same. Regular hetero-associative uses Hebbian rule in the learning phase. The connection weights to store training vector pairs $(s,t)$ are computed as Algorithm 1, in which $s$ shows the input vector while $t$ is used as an output vector [1].

**Algorithm 1.** Hetero-associative learning procedure.

**Data**: input pattern: $x$, output pattern: $y$
**Result**: Weight matrix : $w$
*Step* 0: Initialize all weights:
$w_{ij}=0.\ (i=1,\ \dots,\ n\ ;\ j=1,\ \dots,\ m)$
*Step* 1: For each input/output training pair $s{:}t$, do steps 2–4.
*Step* 2: Set activations for input units to current training input $x_i=s_i$.
*Step* 3: Set activations for output units to current target output $y_j=t_j$.
*Step* 4: Adjust the weights
$w_{ij}\ (\text{new})=w_{ij}\ (\text{old})+\ x_i\ y_j$

Algorithm 1 shows that the weights can be described in terms of products of the input/output vector pairs to store a set of P association patterns $s(p){:}t(p)$, $p=1,\dots,P$ where

$$s(p)=(s_1(p),\dots s_i(p),\dots s_n(p))$$

$$t(p)=(t_1(p),\dots t_j(p),\dots t_m(p))$$

The weight matrix $W=(w_{ij})$ is given by

$$w_{ij}=\sum_{p=1}^{P}s_i(p)t_j(p) \tag{1}$$

where $x_i$ denotes the $i$th element of input training pattern and $y_j$ is the $j$th element of output pattern. $w_{ij}$ is the connection weight between neuron $i$ and $j$. After learning phase, the network can recall each output pattern using related input samples as shown in the following equations. $f(\cdot)$ is a suitable activation function, if the target responses of the net are bipolar it can be defined as

$$y_{in_j}=\sum_{i=1}^{n}x_iw_{ij} \tag{2a}$$

$$y_j=f(y_{in_j}) \tag{2b}$$