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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
$w_{ij}\ (\mathrm{new})=w_{ij}\ (\mathrm{old})+\ x_i\ y_j$

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 $s(p)$:$t(p)$, $p=1,\ldots,P$ where

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

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

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 ith element of input training pattern and y_j is the jth 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

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

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

$$f(x)=\begin{cases}1, & x\geq 0\\ -1, & x<0\end{cases} \tag{2c}$$

4. S-GCM model description

Ishii et al. have proposed S-GCM model based on Kankos GCM model in order to generate richer dynamics due to introduction of a symmetric map as an activation function. This feature helps the proposed network to be able to mimic chaotic behavior of real brain. Dynamic behavior of chaotic units in this model is described by the following equations [22]:

$$x_i(t+1)=(1-\epsilon)*f[x_i(t)]+\frac{\epsilon}{N}\sum_{(j=1)}^{N} f[x_j(t)] \tag{3}$$

$$f(x)=\alpha x^3-\alpha x+x \tag{4}$$

where $x_i(t)$ denotes the ith units internal state at discrete time t. N stands for the number of units in Eq. (4). α is the bifurcation parameter that controls the strength of chaos in the system. ϵ is the coherent parameter and indicates the strength of coupling which is considered constant in this model. Each unit dynamics is given by the cubic function $f(\cdot)$ which is a symmetric logistic map and can be chaotic or stable that depends on the value of its bifurcation parameter. As α becomes larger, the system dynamic becomes more chaotic and as it decreases, the system dynamic becomes coherent. For example, the system can converge to a fixed point if $\alpha=3$ or can behave periodically for $3.1\leq\alpha\leq 3.5$, it also acts chaotically when $\alpha\geq 3.6$. Fig. 1 shows S-GSMs largest Lyapunov exponent for various parameter values [22]. Ishii represents a new version of S-GCM by modifying Eqs. (3) and (4) as

$$x_i(t+1)=(1-\epsilon)*f_i[x_i(t)]+\frac{\epsilon}{N}\sum_{(j=1)}^{N} f_j[x_j(t)]$$

$$f_i(x)=\alpha_i x^3-\alpha_i x+x \tag{5}$$

Ishii adds update procedure for each unit, based on units energy as an extension of S-GCM model. The evolution of bifurcation parameter α_i can be described as follows where α_{min} is the minimum value of bifurcation parameter [22]

$$\alpha_i(t+2)=\alpha_i(t)+[\alpha_i(t)-\alpha_{min}]*\tanh(\beta*E_i(t)) \tag{6}$$

$$E_i(t)=-x_i(t)*\sum_{j=1}^{N} w_{ij}*x_j(t) \tag{7}$$

α_i would be checked after each update to make sure that it remains bounded between α_{min} and α_{max}. $[w_{ij}]$ is the correlation matrix and is computed in learning step based on Hebbian rule. $E_i(t)$ is the energy of ith unit and is used as a measurement to determine if the internal state of unit matches the correlation matrix W or not. If E_i gets high and positive, the internal state of unit i would not match with correlation matrix. In this case as Eq. (3) shows, α_i parameter increases, and as a consequence result, the unit acts chaotically in order to go to another state for finding a better solution using chaos searching. On the other hand, If E_i gets low and negative, then the internal state of unit would match the correlation matrix. In that case α_i decreases and the unit mode changes stable state. When each partial energy E_i becomes small and negative, α_i will be stable at α_{min}. At this moment, system converges to the best related attractor.

The main strategy of constructing associative memory using S-GCM method is based on using an N-dimensional binary coding function C which is used to convert internal state $x\in[-1,1]^N$ to a binary vector $C(x)=\in\{-1,1\}$ that is defined as [22],

$$C(x)=\begin{cases}1, & x_i>x^*\\ -1 & \text{otherwise}\end{cases} \tag{8}$$

where x^* denotes the fixed point of logistic map and it is equal to zero ($x^*=0$). The N dimentional function V converts a binary vector $I\in\{-1,1\}^N$ into a state vector $I(x)\in[-1,1]^N$ as [22]

$$V(I)=\begin{cases}x^+, & I_i=1\\ x^-, & I_i=-1\end{cases}$$

where $0<x^+<1$ and $-1<x^-<0$ are random values. The general strategy of S-GCM to generate the output pattern O related to the input pattern I is as follows [22]:

$$I\xrightarrow{v}x(0)\xrightarrow{S-GCM}x(T)\xrightarrow{c}O$$

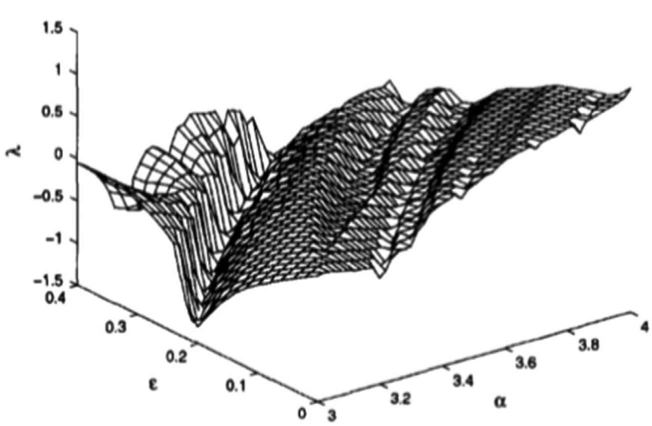

Fig. 1. Largest Lyapunov of S-GCM model [22].

5. Proposed method

In this section, we explain the proposed chaotic hetero-associative in detail. Three stages are given as follows: (1) Structure of proposed method. (2) The proposed learning method (LCLE). (3) Chaotic pattern recall.

When a new pattern is given to the network, the network updates its weights based on LCLE method to learn the new pattern. In the recall process when a noisy input data is given to the network, neurons show a chaotic behavior in order to converge to the related associated pattern.

5.1. The structure of our proposed method

The chaotic hetero-associative memory includes two sets of neurons. First layer neurons are used to reconstruct noisy inputs and second set is used to recall output patterns. The structure of the proposed method is shown in Fig. 2. x_i shows ith external input element and y_j indicates jth element of network output. We use two weight vectors in our proposed structure. The first weight vector W^1 consists of connections strength between input neurons is called input weight and is used in input patterns reconstruction. W^1 can be trained by Hebbian rule. The input neurons act chaotically to reconstruct input patterns. The second weight vector W^2 carries the correlation between related input and output patterns based on our proposed learning method which is reported in the next section. The outputs of input neuron layer are sent to output neurons through this weight vector W^2.

5.2. The LCLE learning method

One of the disadvantages of regular hetero-associative memory is low storage capacity. Although we can make regular hetero-associative

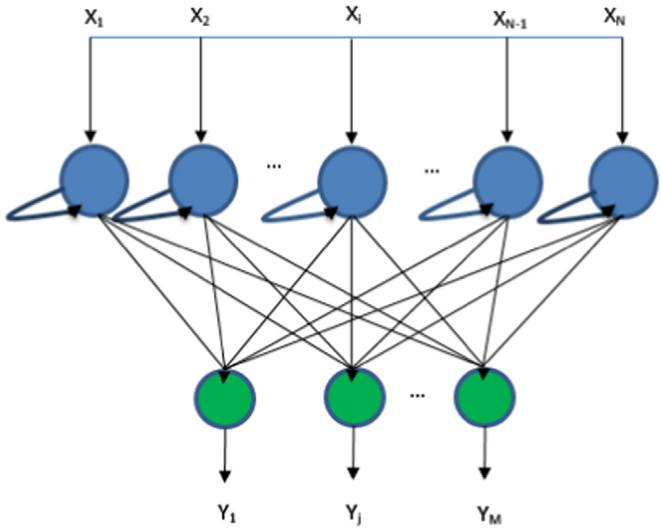

Fig. 2. The structure of LCHAM method.

memory which is able to store more patterns using more neurons, it causes less efficiency and low speed. We extended sparse learning method based on importance of input/output correlation [2] to overcome low storage capacity. Moreover, regular hetero-associative memory cannot store a new pattern after its training phase, but in real world our brain can learn new things without need to retrain previous data [1]. Our LCLE learning method is also able to provide successive learning, even after training phase or during recall step. The LCLE weight matrix is represented by

$$w_{ij} = w_{ij} + \sum_{i=1}^{D_1} \sum_{j=1}^{D_2} \frac{1}{N} \prod_{k=1}^{N} (x_i^k + y_j^k + \epsilon)^2 \tag{9}$$

where x_i is the ith element of kth input learning pattern, y_j is the jth element of kth output learning pattern and N is the number of patterns. D_1 is the dimension of input patterns and D_2 denotes the dimension of output patterns. As Eq. (9) shows, each weight element w_{ij} is computed according to the correlation between element i and j along all input and output learning patterns. We divide ϵ as a small value (and 0.2) in Eq. (9) in order to avoid w_{ij} to be zero when the correlation of two elements in one of the related input/output patterns is zero. Without this parameter, the network is not able to save weak and strong correlations and it only saves binary weights. On the other hand we proposed Less Correlation Less Effect (LCLE) to overcome the policy of less correlation no effect which sparse learning method does.

5.3. Chaotic pattern recall

In recall step, input neurons act chaotically based on S-GCM model which is reported in Section 4 in order to reconstruct networks input. Then the reconstructed input is sent to output neurons through LCLE weights to recall the related output pattern. In the next section, the great effect of this dynamic behavior on recall process is shown.

6. Experimental result

In this study, letters are employed as learning patterns. Each input pattern comprises 10*10 binary pixels and each output associated pattern is a 5*5 binary square matrix. Some example could be seen in Figs. 3 and 4, where a white pixel is coded by value of 1 and a black pixel is given a value of −1.

Fig. 3. Stored input patterns.

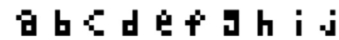

Fig. 4. Associated output patterns.

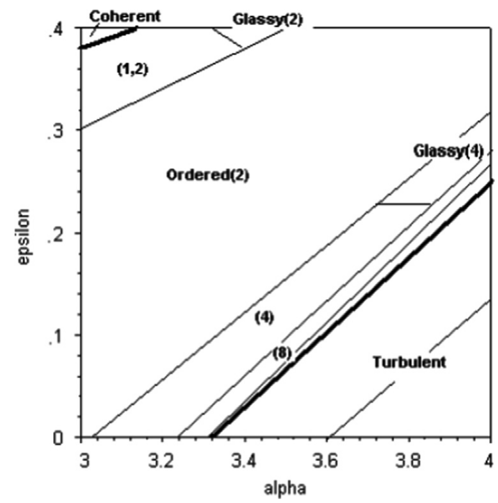

Fig. 5. Phase diagram of S-GCM [22].

Correspondingly, the network is constructed with 100 neurons in input layer and 25 neurons in output layer.

As stated before in Sections 4 and 5, S-GCM could be chaotic or stable based on its parameters. According to Fig. 5 where Ishii et al. presented about dynamics of logistic map based on its control parameters α, ϵ [22], it can be seen when $\epsilon = 0.1$, changing α would make S-GCM stable or chaotic. changing α from 3 to 3.3 while ϵ is equal to 0.1 does not change S-GCM, but it can be chaotic if α gets between 3.5 and 4. We set the initial values of control parameters as $\alpha = 3.6$, $\epsilon = 0.1$ in order to make our system start from a chaotic state. α parameter is bounded to its upper bound and its lower bound $3 < \alpha < 4$ to control systems dynamics and make sure the energy function could control system chaos.

Fig. 6 illustrates the time series of alpha parameter evolution. It can be seen that the α_i parameter is high for each unit at early iterations to find the best value of ith input index due to finding possible minimum energy as time elapses. The unit motions become stable after chaotic searching by decreasing the value of chaos control parameter.

Units energy in each iteration is computed and shown in Fig. 7. It can be seen that at early iterations each partial energy changes chaotically because of high energy and as time elapses energy changes to find the best ith input index as well as minimum energy. Finally, each partial energy will be stable at a small and negative value and the system will converge to its possible minimum energy.

The simulation results show that the proposed structure improves storage capacity of hetero-associative memory as twice as a regular hetero-associative memory in perfect recall. Depending on training letters as associated patterns, conventional hetero-associative memory can recall perfectly 3–4 patterns which is as half as proposed method which can recall perfectly 7–8 associated patterns. Performance of regular associative memory and the proposed method for a different size of data set are shown in Fig. 8. As size of data-set gets larger, the proposed method gives a more accurate performance than regular hetero-associative memory. The proposed method was also compared with Lattice hetero-associative memory. In Fig. 8 performance recall of Lattice

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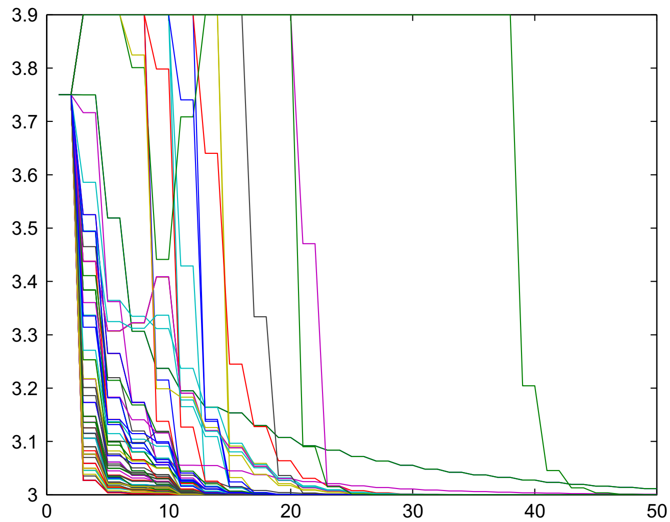

Fig. 6. Time series of *alpha*.

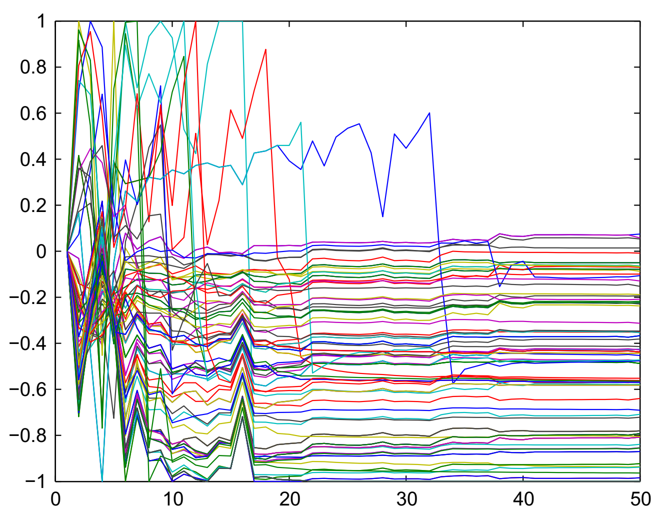

Fig. 7. Time series of energy.

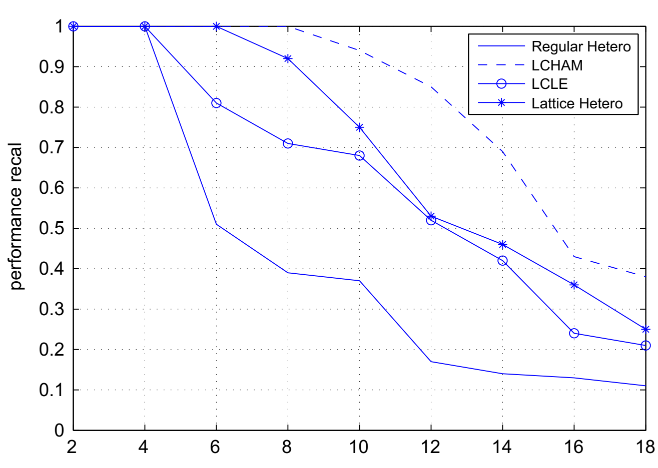

Fig. 8. Recall performance for different number of training pairs.

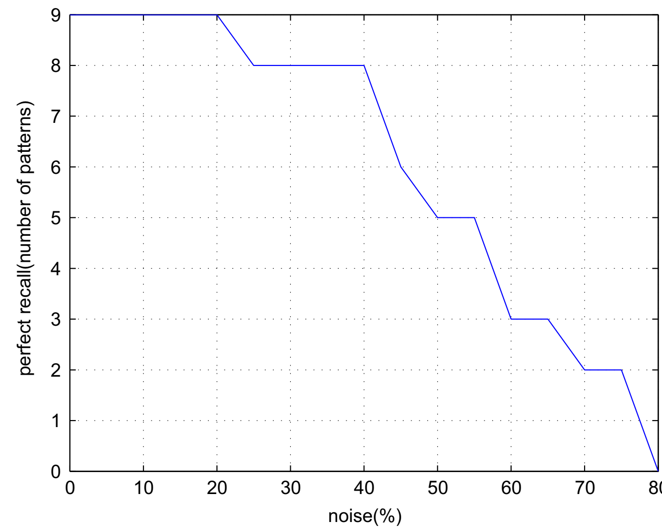

Fig. 9. Recall performance for perfect recall in the presence of noise.

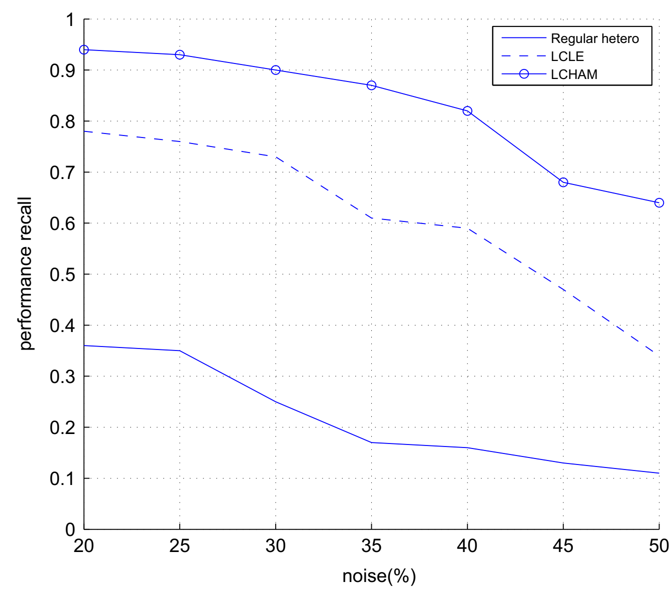

Fig. 10. Recall performance for 10 training pairs while noise percentage is changing from 20% to 50%.

hetero-associative memory based on the number of training stored patterns is shown. Lattice associative memories are expected to have a high storage capacity in comparison with conventional ones, however, Fig. 8 shows that the proposed method is able to store even more associated patterns than Lattice hetero-associative memory. Although Lattice associative memories seems extremely powerful, Lattice hetero-associative memory has multiple weaknesses which Lattice auto-associative would not suffer from [9]. This higher storage capability and also being robust to noise would be both advantages of the proposed method over other hetero-associative memories.

Fig. 9 shows the perfect recall ability of the proposed method with the presence of noise from 0% to 80%. Robustness against noise is the most important feature that chaos can add to LCHAM model. To evaluate the effectiveness of our proposed method, we add random noise to input data in different levels and give them as test set to the network. Fig. 10 shows the result of comparing LCHAM with regular hetero-associative memory and a hetero-associative based on LCLE learning. As it has been shown, the proposed method represents the most efficient solution in compared models while the difference is noticeable when noise increases.

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Fig. 11 shows a comparison of the LCHAM, chaotic BAM network [23], the Kosko BAM (KBAM) network [24] and also the pseudo-inverse technique ($W = X(X^TX)^{-1}Y^T$) [25] for 10 training pairs which shows clear superiority of the proposed model over the others for different noise percentages of eight input patterns.

Fig. 12 shows 3 different examples of noisy input and their corresponding output recall to express the robustness of the model. Fig. 13 shows convergence evolution of input samples "B" and "G". Corresponding output patterns of input samples are presented in Fig. 14 "b" and "g". As it is shown in Fig. 15, regular hetero-associative memory is not able to generate desired output pattern of input samples "B" and "G" in Fig. 13 because of its limited capacity. A regular associative memory with N neurons can store at most 0.135 N patterns so if we train it for 10 patterns as an example, it could not be able to recall most of the patterns correctly [22].

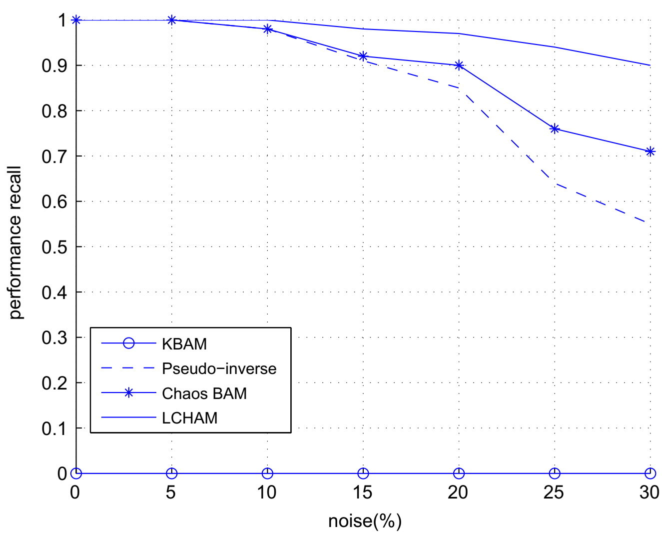

Fig. 11. Recall performance for 8 training pairs while noise percentage is changing from 0% to 30%.

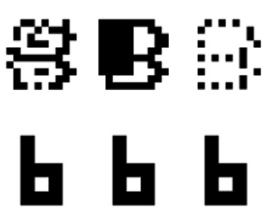

Fig. 12. Final recall of 3 different noisy input samples.

7. Conclusion

In this paper, we proposed a chaotic hetero-associative memory which is able to store and recall a set of associated patterns even if they are noisy or corrupted. Based on our new learning method which is called "Less Correlation less effects" to store all correlations and also using chaotic behavior to make a global search in recall step, our proposed method would have the following features:

- It can store as twice associations as a regular hetero-associative memory.
- It is robust to noise by employing chaotic behavior and can converge to the desired output pattern in the presence with input noise with 20% noise.
- Learning phase and recall step are not divided in this structure and it can learn new associations after learning step without any need to retrain the previous training associations.

Appendix A. Supplementary data

Supplementary data associated with this paper can be found in the online version at http://dx.doi.org/10.1016/j.neucom.2015.04.060.

Fig. 14. corresponding output patterns of B and G in Fig. 13.

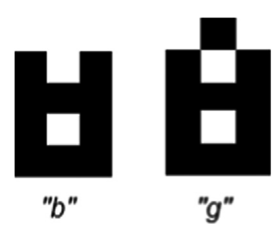

Fig. 15. Output of a regular hetero-associative memory for input patterns "B" and "G" while size of data set is 10.

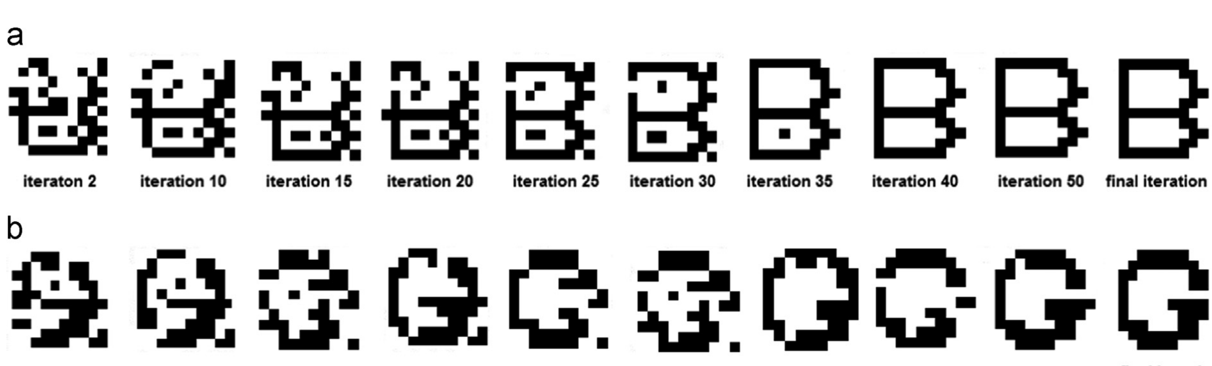

Fig. 13. Evolution process of noisy input samples of training patterns "B" and "G".

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