Extraction of Patterns from a Hippocampal Network Using Chaotic Recall

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Abstract: In neural networks, when new patterns are learned by a network, the new information radically interferes with previously stored patterns. This drawback is called catastrophic forgetting or catastrophic interference. We have already proposed a biologically inspired dual-network memory model which can reduce catastrophic interference. Although two distinct networks of the model correspond to the hippocampus and the neocortex of the brain, the former was modeled by a very simple neural network. In this paper, we improve the hippocampal network of the model and examine its behavior. Computer simulation results show that the proposed hippocampal network has much better ability to store and retrieve training patterns.

Key–Words: Catastrophic forgetting, chaotic neural network, complementary learning systems, dual-network, hippocampus, neurogenesis, neuronal turnover

1 Introduction

It is well known that when a neural network is trained on one set of patterns and then attempts to add new patterns to its repertoire, catastrophic interference, or the complete loss of all of its previously learned information may result. This type of radical forgetting is unacceptable both for a model of human memory and for practical engineering applications. In order to avoid this implausible failure, French [1] and Ans and Rousset [2] independently developed dual-network architectures which are composed of two multilayer neural networks: a hippocampal network and a neocortical network. The hippocampal network is for early-processing and the neocortical network is for long-term storage. In general, once training patterns have been learned by a network, it is natural to assume that the original patterns are no longer available. So, information is transferred back and forth between two networks by means of pseudopatterns in their dual-network models.

Recently, we have also proposed a novel dual-network memory model [6, 7] inspired by the complementary learning systems theory [3]. This model employs a chaotic neural network [4] as the hippocampal network and information transfer from the hippocampal network to the neocortical network is carried out by chaotic recall of the hippocampal network. Since previously learned original patterns can be extracted from chaotic recall, we have shown that the our dual-network model can significantly reduce catastrophic forgetting. However, in this hippocampal network, we have to add some extra elements that take −1 to each training patterns in order to avoid inverted version of training patterns being recalled. This restriction is biologically implausible and we use trial and error to determine how many elements to be added. Moreover, since the hippocampal network is a Hopfield network (with chaotic neurons), as is well known, its storage capacity is extremely low.

In this paper, we propose a novel hippocampal network for the dual-network memory model and examine its ability to recall stored training patterns by chaotic recall. The proposed hippocampal network is much more biologically plausible than the conventional networks. Its structure is based on the hippocampus of the brain. Moreover, we introduce neurogenesis or neuronal turnover into the hippocampal network based on our recent research [5]. Computer simulation results show effectiveness of the proposed hippocampal network.

2 Conventional Dual-Network Memory Model Using Chaotic Neural Network

Figure 1 shows the structure of the our conventional dual-network memory model [6, 7]. It consists of
two coupled neural networks: a hippocampal network and a neocortical network. The hippocampal network implemented by a chaotic neural network [4] is for early-processing and the neocortical network is for long-term storage. That is, a new input is given to the hippocampal network and is stored there at first, then information stored by the hippocampal network is transferred to the neocortical network (memory consolidation).

Figure 1: Structure of the conventional dual-network memory model [6, 7].

It is known that chaotic neural networks can dynamically retrieve stored patterns from a random input. So, previously learned original patterns can be extracted from chaotic recall in the hippocampal network. In order to transfer information from the hippocampal network to the neocortical one without severe catastrophic forgetting, extracted patterns are learned by the neocortical network with neocortical pseudopatterns. A set of neocortical pseudopatterns is created by a random input and the output of the neocortical network after that input has been sent through it. Since this set of pseudopatterns reflects the previously learned patterns, new patterns extracted from the hippocampal network are interleaved with previously learned information. Hence, catastrophic forgetting can be reduced.

However, in refs. [6, 7], it was necessary to add elements which take $-1$ to each training pattern. Figure 2 shows an example of training patterns for the conventional hippocampal network. In order to avoid inverted version of training patterns being recalled, these extra elements which take $-1$ have to be cramped during recall. This restriction is not only biologically implausible but also undesirable because we must use trial and error to determine the number of extra elements. Moreover, since the conventional hippocampal network is a Hopfield network, its storage capacity is very low, especially for very similar patterns.

3 Anatomical Background

Here, we briefly review the hippocampal architecture and neurogenesis in DG.

3.1 Structure of Hippocampus

As shown in Fig. 3, the hippocampus consists of DG and CA, and CA is divided mainly into CA1 and CA3. DG consists of granule cells, while CA3 and CA1 consist of pyramidial cells. Entorhinal Cortex (EC) which is adjacent to the hippocampus works as an interface to the hippocampus. External input is given to the hippocampus from the second layer of EC, and output of the hippocampus is given to the fifth layer of EC. Neurons of each region are connected with each other. The connection between EC and every region is called Perforant Path (PP). The connection from
CA3 to CA1 is called Schaffer Collateral (SC), and that from DG to CA3 is Mossy Fiber (MF). This connection is known as very sparse and powerful. CA3 has recurrent connection from CA3 to itself, which is called Recurrent Collateral (RC).

External input is given to the hippocampus via EC, and it is sent to each region through PP, MF, SC and RC. Electrophysiological experiment has revealed that the dominant path in learning and that in recall is different [9]. The path, EC→DG→CA3→CA1 is dominantly used during learning. In contrast, the path, EC→CA3→CA1 is dominantly used during recall. Therefore, DG becomes dominant only when learning. In addition, neurogenesis occurs only in this region of the hippocampus.

3.2 Neurogenesis

Neurogenesis in DG of the human hippocampus was discovered in 1998 by Erikson and Gage [10]. Figure 4 shows the process of neurogenesis in DG. DG consists of the granule cell layer and the subgranular zone. First, precursor cells in the subgranular zone divide asymmetrically. Following division, one cell remains in the subgranular zone and retains the capacity to proliferate, and the other cell moves the granule cell layer of DG and grows up. Most of the newly born cells that enter the granule cell layer acquire neuronal characteristics [10].

According to the investigation of Cameron and McKay, about 9,000 new cells are generated per day in the adult rat DG, and the survival rate of generated cells is about 50% with 5-12 days [11]. Since the number of granule cells in the rat DG can be estimated about a million, the rate of neuronal turnover is about 0.45% per day. While, according to the data of young adult rats (35-days-rats), new cells were born about 10,000 per day, and 70% survive two weeks, suggesting a daily neuronal turnover rate of about 1% [12].

4 Novel Hippocampal Network

Here, we propose a novel hippocampal network for the dual network memory model.

4.1 Architecture of Hippocampal Network

Figure 5 shows the structure of the proposed hippocampal network. The model consists of five layers: Input, EC, DG, CA3 and Output. While CA3 is composed of chaotic neurons, other layers are composed of McCulloh and Pitts neurons. Table 1 shows the number of neurons and the firing rate in the model. These data are based on physiological findings and are the same as those shown in [5, 8]. The number of neurons firing in each region is decided by the k-winner-take-all manner [8] based on the firing rate of each region. Although states of neurons in Input and Output layers are represented by bipolar mode, ±1, states of other neurons are represented by binary mode, 0 or 1 [5, 8].

![Figure 5: Structure of the proposed hippocampal network.](image)

Table 1: Details of each region in the hippocampal network.

<table>
<thead>
<tr>
<th>Region</th>
<th>EC</th>
<th>DG</th>
<th>CA3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of neurons</td>
<td>240</td>
<td>1600</td>
<td>480</td>
</tr>
<tr>
<td>Firing rate (%)</td>
<td>10.0</td>
<td>1.0</td>
<td>4.0</td>
</tr>
</tbody>
</table>

4.2 Learning

Although connection weights between Input and EC are fixed at 1, other weights are learned as follows.

EC–DG, EC–CA3, DG–CA3 Connection weights are learned by Oja’s rule [13]:

$$w_{ij}(t + 1) = w_{ij}(t) + \eta y_j (x_i - y_j w_{ij}(t))$$ (1)

where $x_i$ shows the output of a neuron in a layer, $y_j$ shows that in the subsequent layer, $w_{ij}$ denotes the connection weight between these neurons, and $\eta$ is the learning rate.
CA3 Weights are learned by the following Hebbian learning with forgetting [6, 7]:

\[ w_{ij}(t + 1) = \gamma w_{ij}(t) + x_i x_j \tag{2} \]

where \( w_{ij} = w_{ji}, w_{ii} = 0 \) and \( \gamma \) denotes the forgetting factor \((0 < \gamma < 1)\). Owing to use of \( \gamma \), only patterns recently given remain in the hippocampal network.

CA3–Output Weights are learned by the Hebbian learning with forgetting:

\[ w_{ij}(t + 1) = \gamma w_{ij}(t) + x_i y_j \tag{3} \]

where \( x_i \) and \( y_j \) show the output of the \( i \)th neuron in CA3 and that of the \( j \)th neuron in Output, respectively.

4.3 Recall

Based on the evidence from electrophysiological experiment [9], only the path, Input→EC→CA3→Output is used in recall. Moreover, since CA3 is composed of chaotic neurons, the dynamics of the \( i \)th neuron in CA3 is represented by the following equations [4]:

\[ x_i(t + 1) = f\{\eta_i(t + 1) + \zeta_i(t + 1)\} \tag{4} \]

\[ \eta_i(t + 1) = k_m \eta_i(t) + \sum_{j=1}^{N} w_{ij} x_j(t) \tag{5} \]

\[ \zeta_i(t + 1) = k_r \zeta_i(t) - \alpha x_i(t) + a_i \tag{6} \]

where \( x_i(t + 1) \) shows the output of the \( i \)th neuron at \( t + 1 \), \( k_m \) and \( k_r \) are damping factors of refractoriness, \( \alpha \) is a scaling factor of the refractoriness, \( a_i \) is an external input parameter, \( N \) is the number of neurons, and \( f(\cdot) \) show the following output function:

\[ f(u) = \frac{1}{1 + \exp(-u/\epsilon)} \tag{7} \]

where \( \epsilon \) is the steepness parameter.

In the chaotic neural network, states of the network tend to remain in trained patterns for a relatively long period during chaotic recall. Therefore, we can extract stored patterns by a random input, observing chaotic recall and choosing states recalled for a long period.

4.4 Neuronal Turnover

Neuronal birth and extinction, namely neuronal turnover has been modeled as follows [5]. Assume that the rate of neuronal turnover is set to \( \beta \% \). First, \( 0 < \gamma < 1 \) of neurons are chosen randomly in DG. Then the connection weights of those neurons are initialized according to the connection rates in EC–DG and DG–CA3.

5 Computer Simulation Results

In computer simulation, we used the following parameters: \( \eta = 0.1, \gamma = 0.7, k_m = 0.10, k_r = 0.95, \alpha = 2.0, \alpha_i = 0.8 \) and \( \epsilon = 1.0 \) for Eqs.(1)-(7). The rate of neuronal turnover (\( \beta \)) in DG was set to 50%. The number of neurons in Input and Output layers was set to 49 for training patterns shown in Fig.6, and 100 for random patterns. We didn’t use extra elements for each training patterns for the conventional hippocampal network and the proposed one.

5.1 Performance for Alphabetical Patterns

In this experiment, five sets of training patterns were sequentially learned by the both hippocampal models. The number of patterns in a set was varied from two to five. For example, when the number of patterns in a set was two, \{A,B\}, \{C,D\}, \{E,F\}, \{G,H\} and \{I,J\} were sequentially given to the hippocampal network. Thus, the total number of training patterns was varied from 10 to 25.

After each training set was learned, we examined how well stored patterns could be extracted from a random input by chaotic recall as follows. In chaotic recall, we incremented the time \( t \) after all chaotic neurons updated their states asynchronously. To extract patterns from chaotic recall, a random input is given to the hippocampal network, and then we examined output until \( t = 300 \). Then, we extracted patterns when outputs were unchanged more than 3 times. The performance was measured by the extraction rate: a rate for the number of extracted training patterns against the total number of training patterns. The neuronal turnover was carried out every time after a training set was learned.

Table 2 shows the results of this experiment based on 20 trials. As shown in this table, the performance of the proposed hippocampal network is much better than the conventional model. Especially, the proposed model shows good extraction rate when the number of training patterns is large. This result shows that the proposed hippocampal network has large storage capacity.

<table>
<thead>
<tr>
<th>Number of patterns</th>
<th>Conventional</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 × 5</td>
<td>58.5</td>
<td>100</td>
</tr>
<tr>
<td>3 × 5</td>
<td>43.4</td>
<td>97.7</td>
</tr>
<tr>
<td>4 × 5</td>
<td>39.0</td>
<td>91.0</td>
</tr>
<tr>
<td>5 × 5</td>
<td>26.6</td>
<td>81.4</td>
</tr>
</tbody>
</table>

Figure 7 shows an example of chaotic recall of the conventional hippocampal network when the number
of patterns was 25 and the fifth set of training patterns \{U,V,W,X,Y\} was learned. As shown in the figure, only “Y” was extracted in this case. “X” was recalled at \(t = 29\), but it was not stable. Moreover, many spurious states including inverted version of “X” and “Y” were recalled and extracted. When the number of training patterns in a set becomes large, this tendency becomes more conspicuous.

Figure 7: An example of chaotic recall of the conventional hippocampal network until around \(t = 100\).

In contrast, the chaotic recall of the proposed hippocampal network is very stable as shown in Fig.8. Owing to the effect of the forgetting factor \(\gamma\) in Eqs.(2) and (3), although patterns recently learned were often recalled, the extraction of stored patterns was much more stable than the conventional model. In addition, it seems that the spurious memories are much reduced in the proposed model. These characteristics may come from the sparse coding carried out in CA3.

Figure 8: An example of chaotic recall of the proposed hippocampal network until around \(t = 100\).

5.2 Performance for Random Patterns

Here, we examined the relation between the extraction rate and the correlation of patterns by using random patterns. In this experiment, five sets of training patterns were sequentially learned and the number of patterns in a set was set to two and five. We defined the correlation of training patterns as follows:

\[
\text{correlation} = \frac{1}{P C_2} \sum_{m=1}^{P-1} \sum_{n=m+1}^{P} |\mathbf{x}^{(m)\top} \mathbf{x}^{(n)}| \tag{8}
\]

where \(\mathbf{x}^{(m)}\) shows the \(m\)th training pattern and \(P\) shows the number of training patterns. The results are summarized in Tables 3 and 4 based on 20 trials.

<table>
<thead>
<tr>
<th>Correlation of patterns</th>
<th>Conventional</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.50</td>
<td>24.5</td>
<td>99.5</td>
</tr>
<tr>
<td>0.60</td>
<td>13.0</td>
<td>100</td>
</tr>
<tr>
<td>0.70</td>
<td>5.5</td>
<td>98.0</td>
</tr>
<tr>
<td>0.80</td>
<td>3.5</td>
<td>86.5</td>
</tr>
</tbody>
</table>

Table 3: Extraction rate (%) for \(2 \times 5\) random patterns.

<table>
<thead>
<tr>
<th>Correlation of patterns</th>
<th>Conventional</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.50</td>
<td>8.8</td>
<td>81.8</td>
</tr>
<tr>
<td>0.60</td>
<td>0.0</td>
<td>75.4</td>
</tr>
<tr>
<td>0.70</td>
<td>0.0</td>
<td>61.8</td>
</tr>
<tr>
<td>0.80</td>
<td>0.0</td>
<td>50.6</td>
</tr>
</tbody>
</table>

Table 4: Extraction rate (%) for \(5 \times 5\) random patterns.

As shown in these tables, even when the training patterns to be stored are very similar each other, the proposed hippocampal model shows much better extraction rate. According to our past research on the effect of neuronal turnover [5], the similarity of input patterns is much reduced with neuronal turnover in DG. As a result, patterns difficult to learn can be successfully stored and recalled. Thus, the proposed hippocampal network showed much better performance than the conventional one.

Finally, we examined the performance of the conventional hippocampal model when the number of neurons was set to 620. In this case, the total number of connections in the conventional network is 383,780. This is comparable to the total number of connections in the proposed network: 388,039 for learning and 376,519 for recall. In this experiment, we set \(\alpha = 25.0\) for Eq.(6). The results are shown in Table 5 based on 20 trials. Although the performance of the conventional model was slightly improved, that of the proposed one shown in Tables 3 and 4 is still much better. This means that the architecture of the pro-
posed network is essential for superior performance shown in the simulation results.

Table 5: Extraction rate (%) for the conventional model when 620 neurons were used and correlation of patterns was set to 0.50.

<table>
<thead>
<tr>
<th>Number of patterns</th>
<th>Extraction rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$2 \times 5$</td>
<td>35.5</td>
</tr>
<tr>
<td>$5 \times 5$</td>
<td>12.6</td>
</tr>
</tbody>
</table>

6 Conclusions

In this paper, we have proposed a novel hippocampal network for dual-network memory model. The structure of the proposed hippocampal network is based on that of the hippocampus of the brain. Moreover, neuronal turnover and chaotic neural network are implemented in DG and CA3, respectively. Computer simulation results show the following features of the proposed hippocampal network:

1. It shows much better performance for extracting stored patterns by chaotic recall than the conventional hippocampal network.
2. It doesn’t need any extra elements for avoiding inverted version of training patterns being recalled.
3. It is much robust for highly similar training patterns than the conventional network.
4. It has larger storage capacity than the conventional network.

In the future research, we will examine other characteristics of the proposed hippocampal model such as precise storage capacity, noise reduction effect and so on. Moreover, we will examine the ability to reduce catastrophic forgetting by introducing the proposed hippocampal network into the dual-network memory model [6, 7].

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