A dynamic associative memory system by adopting amygdala model

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Abstract: Although several kinds of computational associative models and emotion models have been proposed, interaction between memory and emotion is almost neglected in those conventional models. This study constructs a dynamic memory system which intends to realize dynamic auto-association, and mutual association of time series patterns more naturally by adopting emotional factor: a function model of amygdale. The output of amygdala is des igned to control recollection state of multiple chaotic neural networks (MCNN) in CA3 of a hippocampus-neocorte x. The efficiency of proposed association system is verified by computer simulation using several benchmark time series patterns.

Keywords: hippocampus, neocortex, amygdala, emotion, associative memory, chaotic neural network

I. INTRODUCTION

A conventional hippocampus-neocortex model [1] introduced multi-layer chaos neural networks (MC NN) [2] into CA3 layer of Ito model [3] to realize the mutual recollection of plural time-series pattern s. However, just like almost traditional associative memory models, there is no any emotion factor in the associative memory model though affection stro ngly concerns with memory formation and recollecti on in the brain[4]. In this paper, a computational m odel of the amygdala [5] is introduced into the stat e control algorithm of each CNN layer in MCNN of the conventional dynamic associative memory sy stem. The signals from CA3 layer of hippocampus are considered to stimulate the orbitofrontal which connects with the amygdala directly, the output o f the amygdala is calculated with the output of the orbitofrontal and it controls the dynamic recollecti on of plural time-series patterns by MCNN. The re sults of simulation using proposed associative memo ry system show better recollection than the conventi onal model.

II. MCNN (CA3)

The conventional model of hippocampus-neocortex is presented by Fig. 1 [1]. The signal flow of the system is: input patterns (Input layer) -> sensory memory (CX1) -> short-term memory (CX2) and intermediate-term memory (*DG*) -> MCNN (*CA*3) -> decoding (*CA*1) -> long-term memory (CX2). The long-term memory is stored in CX2 at last, and as output of system, the stored temporal patterns are recalled when one of the patterns is represented as input.

CA3 layer of hippocampus plays an important role in episode memory, and a model with multiple chaotic neural networks (MCNN) is proposed by our former work [2]. MCNN for CA3 layer is designed for mutual

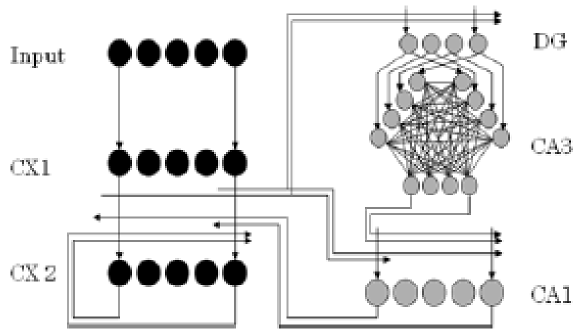

Fig. 1 Hippocampus-neocortex model [1]

association and one-to-many retrieval of time series patterns, using incremental and relational learning between chaotic layers (Fig. 2). The chaotic layers are a kind of traditional chaotic neural networks (CNN) proposed by Aihara *et al.* [6] [7].

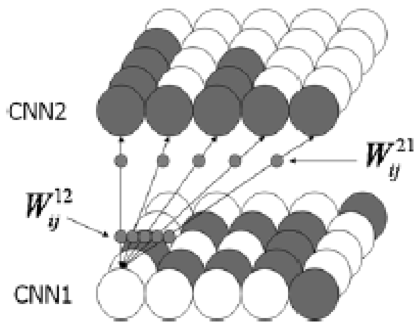

Fig. 2 CA3 layer model (MCNN) [2]

In *MCNN*, neurons on each CNN layer and between the layers connect each other completely, and the dyna mics is as follows:

$$x_i(t+1) = f(y_i(t+1) + z_i(t+1) + \gamma \cdot v_i(t+1)) \quad (1)$$

$$y_i(t+1) = k_r y_i(t) - \alpha x_i(t) + a_i \quad (2)$$

$$z_i(t+1) = k_f z_i(t) + \sum_{j=1}^{n} w_{ij} x_j(t) \quad (3)$$

$$v_i(t+1) = k_e v_i(t) + \sum_{j=1}^{n} W_{ij}^{*} x'(t) \quad (4)$$

where $xi(t)$: output value of ith neuron at time t, n: number of input, wij : connection weight from jth neuron to ith neuron, $yi(t)$: internal state of ith neuron as to factory, $zi(t)$: internal state of ith neuron as to reciprocal action, $vi(t)$: internal state of ith neuron as to reciprocal action from another layer, α: threshold of ith neuron, kf, kr, ke: damping rate, ai: item given by the summation of threshold and external input, γ: the rate of effectiveness from another layer, W^*ij : connection weight from jth neuron of another layer to ith neuron, $x^*j(t)$: output value of jth neuron of another layer at time t.

The conventional network control algorithm of MCNN is shown in Fig.3. The state of a CNN layer is calculated by $\triangle x(t)$, total change of internal state $x(t)$ temporally, and when $\triangle x(t)$ is less than a threshold θ, the chaotic retrieval of the layer is stopped by changing values of parameters kr, kf into zero. The recalled pattern of one CNN layer provides an input pattern to the other CNN layer, and the network realizes mutual association and one-to-many retrieval for plural time series patterns.

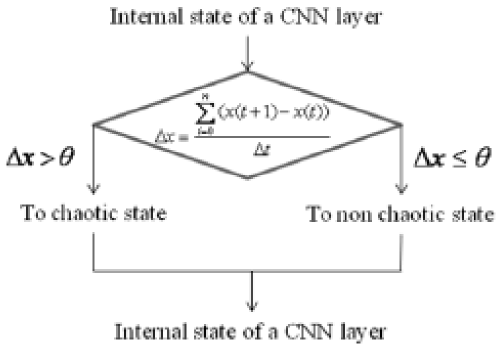

Fig. 3 Recollection process control of MCNN [1] [2]

III. AMYGDALA MODEL

An computational amygdala model [5], which is based on neurophysiological data [8], is shown in Fig.4, The signals from Sensory input to the orbitofrontal cortex which outputs inhibitory value, and the amygdala which provides excitatory value to emotional output of the model. A primary reward signal Rew enters both the amygdaloid and orbitogrontal parts. The dynamics of the model is as follows:

$$A_i = V_i S_i \quad (5)$$

$$O_i = W_i S_i \quad (6)$$

$$E = \sum_i A_i - \sum_i O_i \quad (7)$$

$$\Delta V_i = \alpha(S_i \max(0, \mathrm{Rew} - \sum_j A_j)) \quad (8)$$

$$\Delta W_i = \beta(S_i \sum_j (O_j - \mathrm{Rew})) \quad (9)$$

$$Rew = \begin{cases} 1.0 & \cdots \quad (S > \theta_{AMY}) \\ 0.0 & \cdots \quad (else) \end{cases} \quad (10)$$

where Si: input value of ith neuron, Ai: output value of ith neuron of Amygdala part, Oi: output value of ith neuron of Orbitofrontal part, E: output of the Amygdala model at last, Vi: connection weight from ith neuron at the Amygdala part, Wi: connection weight from ith neuron at the the Orbitofrontal part, Rew: reward of the Amygdala model, α : learning rate of the Amygdale part, β : learning rate of the Orbitofrontal part, θ_{AMY}: threshold of changing Rew.

This model was adopted in an intelligent controller for decision making robust tuning ability [9].

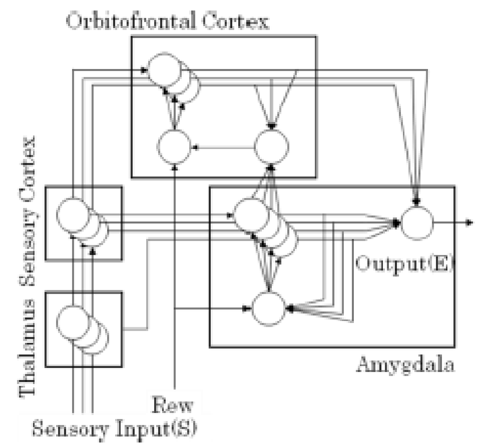

Fig.4 The amygdala model [5].

IV. PROPOSAL MODEL

The hippocampus, the orbitofrontal cortex and and the amygdala are adjacent parts in the limbic system of mammalian brain where concerning deeply with memory and emotion.

Here we suppose that the temporal similarity ofsensory inputs causes decrease of emotion value, and when the emotion value *i.e.* output of the amygdala model is reduced less than a threshold, then the auto-association of one CNN has entered stable state, and its output pattern is used as input pattern of the other CNN layer. The proposal amygdala-hippocampus model of this paper is shown in Fig. 5. The signals from each CNN layers of CA3, i.e. $\triangle x(t)$, enter to the orbitofrontal cortex as inputs, and the outputs of the amygdala model provide the judgement whether or not to change auto-association to relative association by a threshold, *e.g.* zero. The reinforcing signal *Rew* is given by a threshold of sensory inputs (eq. (10)).

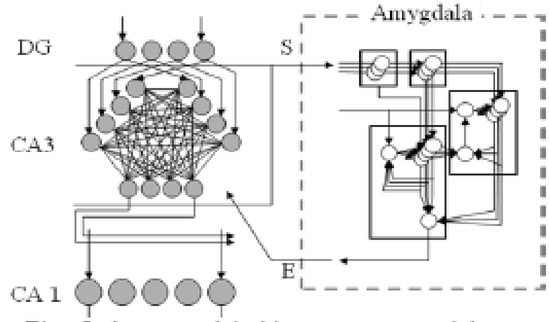

Fig. 5 An amygdala-hippocampus model

IV. COMPUTER SIMULATION

1. Condition

A comparative computer simulation of mutual association was executed between conventional MCNN and proposed model. The input patterns to each CNN layer and its order are shown in Fig. 6. The patterns were used in original CNN's dynamic association simulation also [7]. In MCNN, each CNN layer has relative learning in memory process, and dynamic auto-association in recalling process as shown as in Fig. 7 and Fig. 8.

Parameter of MCNN

$$\alpha = \begin{cases} 1.0 \cdots chaos \\ 0.1 \cdots non-chaos \end{cases}$$

$$k_r = \begin{cases} 0.9 \cdots chaos \\ 0.1 \cdots non-chaos \end{cases}$$

$$k_e = 0.02, k_f = 0.02, \gamma = 0.3, n = 100, \theta = 5.0$$

Parameter of the amygdale model

$$\alpha = 0.2,\ \beta = 0.8,\ \theta_{AMY} = 0.1$$

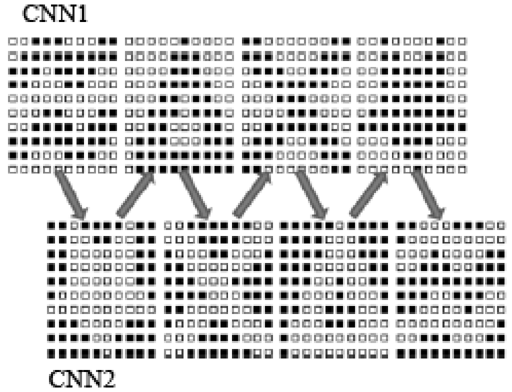

Fig. 6 Input relative patterns

2. The result of simulation

The conventional method started recollection at step 19 and finished all recollections at step 35 (Fig. 7). However, from step 24 to step 33, the change of network was performed from auto-association to relative association, although the four patterns were not recollected completely. Meanwhile, the propose method started recollection from step 9 and completed recollection at step 43 (Fig. 8). All of patterns were completely recalled.

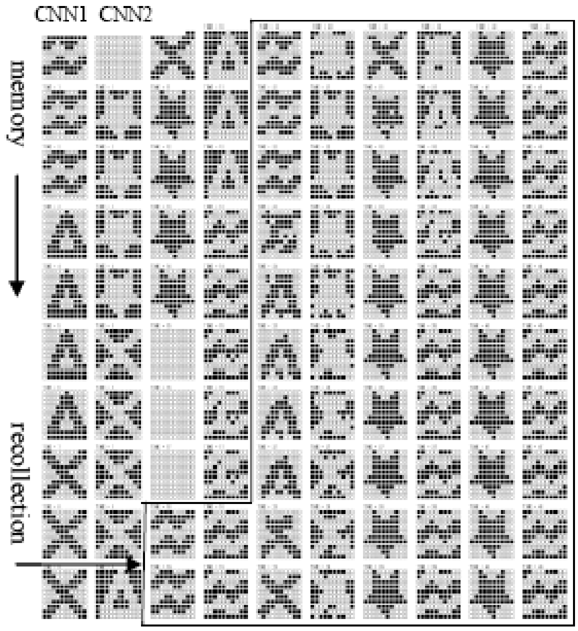

Fig. 7 Result of a conventional model

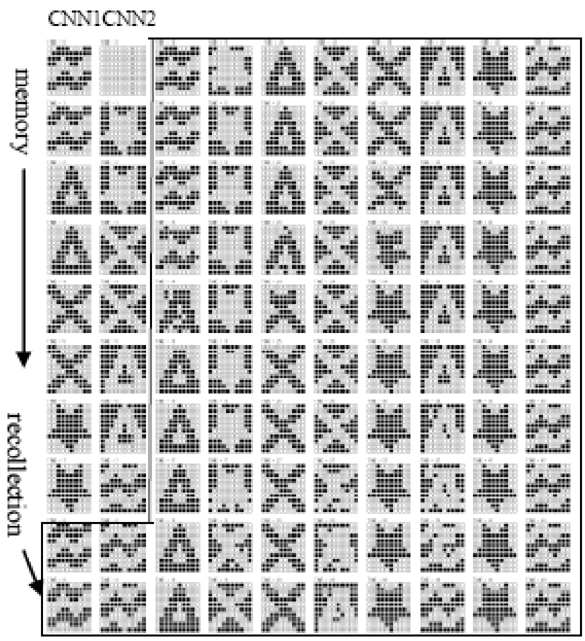

Fig. 8 Result of the proposed model

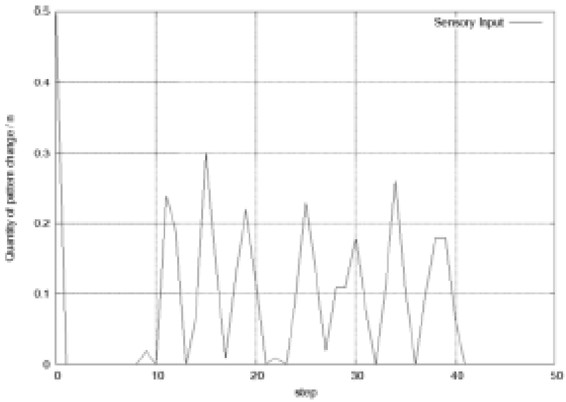

Fig. 9 Input value of the amygdala model

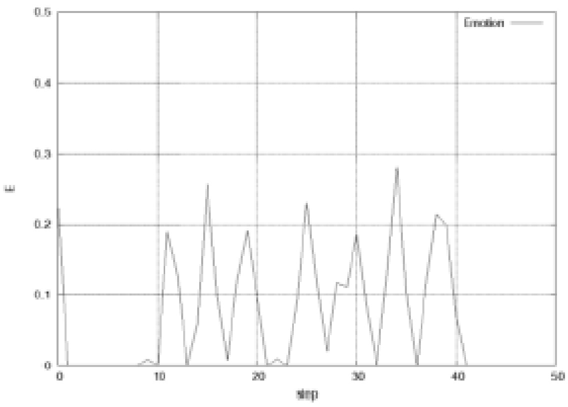

Fig. 10 Output value of the amygdala model

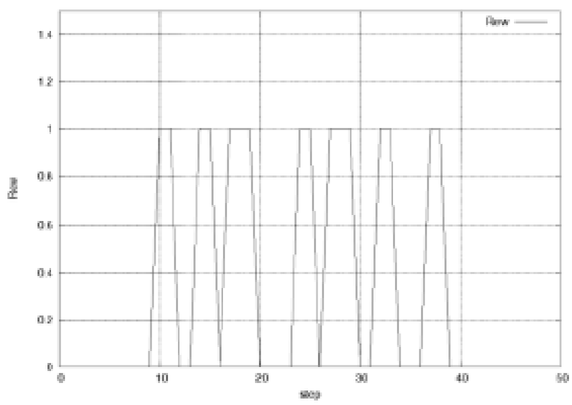

Fig. 11 Reward value of the amygdala model

The input, output and reward value of amygdala model changed with storing and recalling steps are shown in Fig. 9, Fig. 10, and Fig. 11, respectively.

Stronger stimuli of sensory inputs resulted higher reward and emotion value, and the rewards can be confirmed respectively. When the value of emotion reduced to zero, the network changed one CNN layer's recollection to another CNN layer.

V. CONCLUSION

A dynamic associative memory system was proposed by introducing a computational amygdala function model into a conventional hippocampus model MCNN. The emotional model enhances recollection process with more well-grounded based on neurophysiological evidences, and the proposed control method brought better efficient mutual recollections than the conventional one according to simulation results.

The proposed amygdala-hippocampus model is expected to be confirmed its abilities in long-term memory formation process and one-to-many retrieval of plural time series patterns in the future work.

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