

A SINGLE-LAYER ASSOCIATIVE MEMORY WITH FEEDBACK LOOPS APPLIED TO SIMULATING HUMAN BRAIN LIKE ASSOCIATIVE FUNCTIONS

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ABSTRACT A new associative memory is proposed, which can simulate some parts of human memory system. In order to develop the model, several hypotheses are introduced, following biological and psychological aspects. The proposed memory system consists of many memory units, which represent simple and straightforward knowledge. Knowledge is not well structured on memory circuits. Complicated knowledge structure is self-organized in network dynamics. In addition to ordinary associative functions, the following functions, additional learning, self-organizing structured knowledge, forgetting behavior, self-restoration can be performed. Furthermore, psychological behavior, including elaborative rehearsal, typicality, priming effects, inference and so on, can be simulated. Through computer simulation and discussions on comparisons with conventional models, it is confirmed that the proposed model can perform more flexible associative functions.

I INTRODUCTION

An associative memory is one of hopeful applications of artificial neural networks [1],[2]. The following associative functions can be expected. Related matters are recalled from fragmentary information. Common attributes for several articles are retrieved. Furthermore, more human brain like association processes could be expected [3].

In order to realize these functions, several kinds of approaches have been proposed. They include Association [4] and HASP [5], which employ correlation matrices between retrieval keys and matters to be memorized. Memory capacity and noise performance are rather limited. Furthermore, mutually connected neural networks have been applied to this problem. The pieces of knowledge are memorized in the equilibrium states [6],[7]. The model employing asymmetrical weights and variable hysteresis threshold has a large memory capacity and high retrieval rates for noisy stimuli [8]. Another model, employing inhibitory connections in the same category, and excitatory connections through instance units, is also useful for retrieving general and specific knowledge [9]. Furthermore, a spreading activation model also can realize some psychological aspects [10].

The authors have proposed a new associative memory model [11], which belongs to the second category. The following functions can be basically simulated in addition to ordinary associative functions. Additional learning, self-organizing structured knowledge, forgetting behavior, self-restoration, and other psychological behavior of the human memory. In this paper, automatic parameter control, an efficient activation function, and comparisons with conventional models [9],[10] are discussed.

II HYPOTHESES FOR NEW ASSOCIATIVE MEMORY

In order to achieve human brain like associative memories, it is important to take biological and psychological aspects into account. However, most of them have not been cleared. Therefore, some hypotheses must be introduced for constructing an engineering model.

2.1 Knowledge Representation

The following hypotheses are employed for neuron level information representation.

- (II-1) A single neuron represents a single matter, that is local representation.
- (II-2) For a single matter, several neurons are assigned, that is distributed representation.
- (II-3) Relations among matters are expressed by connections. Thus, connection weights express strength of the relations.
- (II-4) Connection weights are adjusted following experience, that is frequency of the corresponding stimuli.
- (II-5) Each neuron has a self-loop in order to hold its state for a while.

2.2 Network Structure and Dynamics

Based on a learning process of human being with fragmentary information, network structure is assumed not to be well organized. Knowledge, represented with neurons and connections, seems to be simple and straightforward. For this reason, the following hypotheses are adopted.

- (II-6) A model consists of many memory units, which represent direct relations among matters.
- (II-7) Knowledge is automatically structured in network dynamics.

In order to simplify hardware and dynamics analysis, the following assumption is employed.
 (II-8) Propagation of signal from one neuron to the other requires a unit delay.

2.3 Unconscious and Conscious Layers

Information processing in the human brain cannot be entirely sensed. Only some part of the processing come to the conscious level. Therefore, we employ the following hypothesis.

(II-9) A model includes unconscious and conscious layers.

2.4 Preprocessing Stimuli

When stimulus "An apple is a red fruit" is given, the following two relations are derived. "Color of an apple is red" and "An apple is a sort of fruit". This kind of preliminary analysis is assumed to be done before applying them to the memory system.

III STRUCTURE OF NEW ASSOCIATIVE MEMORY

3.1 Block diagram

Based on the hypotheses, a new model for an associative memory has been developed. Figure 1 shows a block diagram. Stimuli are applied to the preliminary analysis block. Relations among matters are briefly analyzed here. The analyzed relations are entered into a single layer memory block. The outputs of this block are applied to the unconscious layer. Using nonlinear activation functions, association results are obtained. These results are further transferred to the conscious layer, and at the same time, are feedback to the input of the memory block. The outputs of the conscious layer imply association results, which can be actually sensed. These results are also feedback to the input, in order to cause successive associations.

3.2 Single Layer Memory Block

A square indicates an input unit, which receives stimuli from the primary analysis block, the unconscious and conscious layers, and transmit them to neurons denoted with a circle. Alphabet letters indicate corresponding matters. A single unit represents a single matter. Several neurons are assigned to a single matter. A neuron is assigned to the same matter as the input unit. Connections between the squares and the circles represent relations between matters. Therefore, simple and straightforward relations are only stored on the memory circuits. More complicated relations are equivalently generated through network dynamics. Namely, well structured knowledge is self-organized. Each neuron has a self-loop, in order to hold its state for a while. A sub-block, including a single input unit and several neurons, is called "memory unit". Thus, each memory unit contains a single retrieval key and its related matters.

Network Equations: The input unit receives the stimulus $s_x(n)$ and the outputs of the unconscious and conscious layers $v_{ux}(n-1)$ and $v_{cx}(n-1)$, respectively.

$$u_x(n) = s_x(n) + \beta v_{ux}(n-1) + \gamma v_{cx}(n-1) \quad (1)$$

$$0 < \beta, \gamma < 1, X = A, B, C, \dots$$

The input $net_{xk}(n)$ and the output $a_{xk}(n)$ of the neurons are calculated as follows:

$$net_{xk}(n) = w_{yx}u_y(n) + \alpha a_{xk}(n-1) \quad (2)$$

$$a_{xk}(n) = f_{\Lambda}(net_{xk}(n)) \quad (3)$$

$$0 < \alpha < 1, X, Y = A, B, C, \dots, k=1, 2, \dots$$

w_{yx} is connection weight from the Y input unit to the X neuron. A squashing function is used for $f_{\Lambda}(\cdot)$. Several $a_{xk}(n)$ are gathered at the node \odot .

$$a_x(n) = \sum_k a_{xk}(n-1) \quad (4)$$

3.3 Unconscious and Conscious Layers

From the biological analogy, and stable operation requirement, the following nonlinear and normalized function is introduced.

$$y = f(a_x) = \begin{cases} 0, & |a_x| < \eta a_{max} \\ a_x/a_{max}, & |a_x| \geq \eta a_{max} \end{cases} \quad (5a)$$

$$a_{max} = \max_x \{a_x\} \quad (6)$$

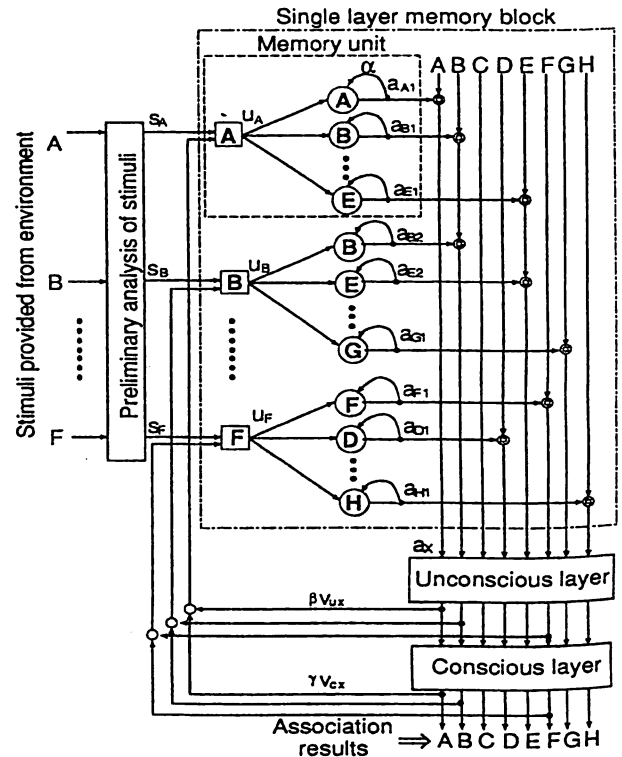


Fig.1 Block diagram for proposed associative memory.

3.4 Parameter Control

How to determine and control the parameters α , β , γ , η , are important points. Because the same control method and values should be widely used. For this purpose, we propose a damping factor for η in Eq.(5). In this method, the other parameters, α , β and γ can be determined in a relatively wide range, and can be fixed. η is given by

$$\eta(n) = \eta_0^n \quad (7)$$

$$0 < \eta_0 < 1$$

3.5 Learning and Associative Functions

Regarding learning algorithm, associative functions and psychological behavior, please refer [11], due to page limitation.

IV SIMULATION AND DISCUSSIONS

4.1 Knowledge to Be Stored and Network Structure

Knowledge listed in Table 1 [2],[9] is used. All articles have their own memory unit, in which the input unit represents each article, and neurons are assigned to the other related articles. Connection weights are all 1. The threshold factor is chosen to be $\eta_0=0.9$, that is $\eta(n)=0.9^n$, based on experience. The other parameters, α and β are chosen to be 0.8, and are fixed. They are not so severe in the association process. The conscious layer is not taken into account, in order to investigate internal operation of the proposed model.

4.2 Association Problems and Simulation Results

The following association functions are simulated. The results are listed in Table 2, in which the stimulus is indicated with #. This table shows the activation level of the input of the unconscious layer after 10 cycles. In the proposed model, the steady state can be obtained during some interval. So, it is easy to detect the association results.

(1) Associate attributes of some person: Stimulus = "Greg". All attributes of "Greg" are highly activated. Furthermore, the other members, who share attributes with "Greg" can be activated, like "Fred".

(2) Associate right persons, who satisfy the given conditions: Stimuli = "Sharks", "20's". "Ken", whose attributes match both stimuli, has the highest activation, and his attributes are also activated to some extent. The latter is indirect association.

(3) Correct wrong information: Stimuli = "Sharks", "20's", "J.H.", "Single", "Burglar". There is no such members, who satisfy all stimuli. The attributes of "Ken" mostly consistent with the stimuli, except for "J.H.". Thus, "Ken" is highly activated. Furthermore, "J.H." is replaced by "H.S.", which belongs to "Ken". This means the wrong information "J.H." is corrected.

(4) Extract general properties of some category: Stimulus = "Jets". The attributes mostly belong to the members of "Jets" are activated.

(5) Infer missing information: Stimuli = "Lance", Missing information = connections between "Lance" and "Burglar". Since many persons, who share the same attributes with "Lance", have the occupation of "Burglar", the occupation of "Lance" is inferred as "Burglar". Thus, missing information can be inferred from the related concepts.

(6) Priming Effects: Preceding stimuli(#) = "Doug", "Neal" applied at n=0

Succeeding stimuli(*) = "Sharks", "Single" applied at n=5

Among members, who satisfy the succeeding stimuli, the members, "Neal", ("Ike", "Nick"), "Ken" are activated in this order. They share many attributes with "Doug", "Neal".

4.3 Comparisons with Other Models

One of the important functions is "additional learnability". The instance unit model [2],[9] and the spreading activation model [10] can realize this function. Due to page limitation, the detailed simulation results for these models are omitted. Their properties are briefly summarized here.

The former model has inhibitory connections among articles belonging to the same category. This

Table 1 Knowledge used in simulation.

Name	Gang	Age	Edu	Mar	Occupation
Art	Jets	40's	J.H.	Sing.	Pusher
Al	Jets	30's	J.H.	Mar.	Burglar
Sam	Jets	20's	COL.	Sing.	Bookie
Clyde	Jets	40's	J.H.	Sing.	Bookie
Mike	Jets	30's	J.H.	Sing.	Bookie
Jim	Jets	20's	J.H.	Div.	Burglar
Greg	Jets	20's	H.S.	Mar.	Pusher
John	Jets	20's	J.H.	Mar.	Burglar
Doug	Jets	30's	H.S.	Sing.	Bookie
Lance	Jets	20's	J.H.	Mar.	Burglar
George	Jets	20's	J.H.	Div.	Burglar
Pete	Jets	20's	H.S.	Sing.	Bookie
Fred	Jets	20's	H.S.	Sing.	Pusher
Gene	Jets	20's	COL.	Sing.	Pusher
Ralph	Jets	30's	J.H.	Sing.	Pusher
Phill	Sharks	30's	COL.	Mar.	Pusher
Ike	Sharks	30's	J.H.	Sing.	Bookie
Nick	Sharks	30's	H.S.	Sing.	Pusher
Don	Sharks	30's	COL.	Mar.	Burglar
Ned	Sharks	30's	COL.	Mar.	Bookie
Karl	Sharks	40's	H.S.	Mar.	Bookie
Ken	Sharks	20's	H.S.	Sing.	Burglar
Earl	Sharks	40's	H.S.	Mar.	Burglar
Rick	Sharks	30's	H.S.	Div.	Burglar
Ol	Sharks	30's	COL.	Mar.	Pusher
Neal	Sharks	30's	H.S.	Sing.	Bookie
Dave	Sharks	30's	H.S.	Div.	Pusher

causes some limitation. For instance, the association problem (2) in the previous section, "Fred" is associated from "Greg" due to their common attributes. However, this kind of association is impossible in the instance unit model due to inhibitory connection from "Greg". Furthermore, the priming effects (6) is also impossible from the same reason.

The spread activation model has another difficulty. Since the activation propagates over the network, the optimum association results are obtained at very limited cycle numbers. In other words, this model cannot provide the steady state for a while. There is no way to know when the results should be detected in advance.

Based on the simulation results and discussions on comparisons in this section, the proposed model has very flexible and powerful associative functions.

V CONCLUSIONS

This paper presents a new associative memory. The structure is a single-layer network with feedback loops. This model consists of many memory units, which represent simple and straightforward knowledge. Complicated knowledge structure can be self-organized through the network dynamics. The threshold control method has been introduced, which can be widely used. Computer simulation and comparisons with the conventional models show the proposed model can realize a variety of associative functions.

REFERENCES

- [1] T. Kohonen, "Self-Organization and Associative Memory", 3rd ed., Springer-Verlag, 1989.
- [2] D.E. Rumelhart, J.L. McClelland and The PDP Research Group, "Parallel Distributed Processing", The MIT Press, 1986.
- [3] R.L. Klatzky, "Human Memory-Structures and Processes", 2nd ed., W.H. Freeman and Company, 1980.
- [4] K. Nakano, "Associatron-A model of associative memory", IEEE Trans. on S.M.C., vol. SMC-2, no.3, pp.381-388, July 1972.
- [5] Y. Hirai, "A model of human associative processor (HASP)", IEEE Trans on SMC, vol. SMC-13, no.5, pp.851-857, 1983.
- [6] J.J. Hopfield, "Neural networks and physical systems with emergent collective computational abilities", Proc. Natl. Acad. Sci. USA 79, pp.2554-2558, 1982.
- [7] K. Nakayama and M. Tonomura, "A stochastic associative memory using mutually connected neural network", Proc. ISITA'90, Hawaii, pp.639-642, 1990.
- [8] K. Nakayama and N. Mitsutani, "An adaptive hysteresis threshold method for an associative memory using mutually connected neural network", Proc. IJCNN'91, Seattle, vol. II, p.A-914, 1991.
- [9] J.L. McClelland, "Retrieving general and specific knowledge from stored knowledge of specifics", Proc. Third Annual Conf. Cognitive Science Society, 1981.
- [10] A.M. Collins and E.F. Loftus, "A spreading activation theory of semantic processing", Psychological Review, 82, pp.407-428, 1975.
- [11] K. Nakayama and K. Ikehara, "An associative memory self-organizing structured knowledge using fragmentary information", Proc. IJCNN'92 Beijing, pp. II-53-58, Nov. 1992.

Table 2 Association level of each article at n=10.

Symbol # is stimulus given at n=0.

Symbol * is the succeeding stimulus in (6) given at n=5.

Function	(1)	(2)	(3)	(4)	(5)	(6)
Jets	0.717	0.053	0.000	# 1.000	1.000	0.433
Sharks	0.000	# 0.603	# 0.508	0.005	0.000	* 0.526
20's	0.717	# 0.010	# 0.508	0.542	0.785	0.188
30's	0.000	0.079	0.000	0.219	0.135	0.727
40's	0.000	0.026	0.000	0.111	0.071	0.068
J.H.	0.106	0.000	# 0.010	0.542	0.785	0.220
H.S.	0.552	0.546	0.343	0.219	0.135	0.689
COL.	0.053	0.000	0.000	0.111	0.071	0.068
Sing.	0.198	0.493	# 0.508	0.542	0.282	* 0.879
Mar.	0.508	0.026	0.000	0.219	0.509	0.068
Div.	0.000	0.026	0.000	0.111	0.130	0.067
Pusher	0.552	0.053	0.000	0.276	0.206	0.179
Burglar	0.106	0.440	# 0.508	0.276	0.309	0.081
Bookie	0.053	0.053	0.000	0.276	0.141	0.722
Art	0.360	0.109	0.174	0.450	0.408	0.279
Al	0.355	0.109	0.174	0.405	0.546	0.247
Sam	0.366	0.334	0.328	0.450	0.408	0.415
Clyde	0.244	0.109	0.174	0.450	0.408	0.415
Mike	0.244	0.109	0.174	0.450	0.408	0.558
Jim	0.366	0.334	0.339	0.450	0.556	0.144
Greg	# 1.000	0.334	0.164	0.405	0.546	0.241
John	0.530	0.334	0.339	0.450	0.715	0.144
Doug	0.360	0.163	0.164	0.405	0.255	# 0.709
Lance	0.530	0.334	0.339	0.450	# 0.816	0.144
George	0.366	0.334	0.339	0.450	0.339	0.144
Pete	0.535	0.415	0.328	0.450	0.408	0.552
Fred	0.690	0.415	0.328	0.450	0.408	0.410
Gene	0.535	0.334	0.328	0.450	0.408	0.279
Ralph	0.360	0.109	0.174	0.450	0.408	0.416
Phill	0.349	0.279	0.164	0.142	0.236	0.278
Ike	0.122	0.334	0.339	0.228	0.245	0.594
Nick	0.354	0.415	0.328	0.185	0.127	0.588
Don	0.233	0.334	0.328	0.142	0.236	0.278
Ned	0.233	0.279	0.164	0.142	0.236	0.415
Karl	0.349	0.334	0.164	0.142	0.236	0.409
Ken	0.360	1.000	1.000	0.228	0.245	0.455
Earl	0.349	0.415	0.328	0.142	0.236	0.272
Rick	0.238	0.415	0.328	0.142	0.127	0.409
Ol	0.349	0.279	0.164	0.142	0.236	0.278
Neal	0.238	0.415	0.328	0.185	0.127	# 0.745
Dave	0.354	0.334	0.164	0.142	0.127	0.409