### Memory Retention strategy by balancing Neutral Energy Point

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**Abstract:** As Internet related technologies are developing at high speed, the importance of smart Intelligent system which can process dynamic complex information from the data flood is getting high. It has already became a hot issue how to process efficiently huge amount of data having features of large scale, dynamics and complex. In this paper, focusing on the memory management, memory retention and Retrieval strategy by balancing Neutral Energy point adopting the brain function is proposed. This system was applied to the virtual memory and tested with sample data.

Keywords: memory retention, Neutral energy point, Type Matching Data selection, knowledge network

#### **1. INTRODUCTION**

The success of the digital revolution and the growth of the Internet have ensured that huge volumes of highdimensional multimedia data are available all around us. This information is often mixed, involving different data types. It has the characteristics of dynamics, complex and huge amount of data. According to Moore's law, the number of transistors in a single microchip is doubled every 18 months. We can correlate this with a similar observation from the data and information domain. It has already became a hot issue how to process efficiently huge amount of data having features of large scale, dynamics and complex. Many studies for making smarter Intelligent system have been made for many recent years. As one of these branches, the researches adopting the natural phenomena or brain functions have been progressing actively. Especially, the studies of Brain technology are very meaningful from the point of view that human brain is a final product which has been survived and evolved in the dynamic complex environments for several million years. That is, it means that human brain has the optimum structure and functions for facing the dynamic complex environment. Focusing on the memory management, it is known that the brain maintains the optimum status in the neural networks during the process of information storing, retaining, cleaning and retrieving.

In this paper, finding a clue from the brain functions of maintaining the memory, the memory is designed to be composed of knowledge networks with knowledge nodes. Knowledge node has three components of ID name, Type and Internal Energy. Neutral Energy point is also defined and Memory Retention and Retrieval strategy introducing the concept of Neutral Energy point is proposed. This strategy was applied to the virtual memory and experimented with sample testing data.

#### 2. MEMORY DESIGN AND ACTIVATION

In this proposed system, memory was designed to be composed of Knowledge Network which consists of knowledge nodes and their associative relations. Knowledge node has three values of ID name, Type and Self Energy. Fig. 1 shows Memory activation and retention process. The Entering input, $I_i$ , activates type matched knowledge nodes in the Knowledge Network using Type Matching Selection mechanism and changes its value of Self Energy as a memory retention process. Through this activating process, the system extracts the thinking chains related to the Type matched selected knowledge nodes.



Fig. 1 Memory activation and retention

# 2.1 The representation of knowledge node and knowledge network•knowledge node

Knowledge node is an basic atom composing the Knowledge Network. It contains 'Name', 'Type', 'Energy' attributes which can identify itself. Knowledge node is represented as a form of 'struct'.

#### struct k-node<sub>*i*</sub> $\langle Name, Type, Energy \rangle$

The term of Energy describes Self Energy value of [-1.0,1.0] inside the individual knowledge node. The minus value means a negative state and the plus value means a positive state. If the value of Self Energy is zero, it is on the neutral point which represents the balanced state.

#### Knowledge Network

Knowledge Network is connected by associative relations between Knowledge nodes and contain the information. It is represented as

$$\langle \mathbf{K}\text{-node}_i, R_{ij}, \mathbf{K} - node_j \rangle$$

where  $K - node_i$  is the name of knowledge node and  $R_{ij}$  is connection strength between two knowledge nodes.  $R_{ij}$  is calculated by equation (1).

$$\mathbf{R}_{ij} = \mathbf{P}(K - node_i \mid K - node_j) \tag{1}$$

#### 2.2 Type Matching Selection

Type is defined as a factor representing the property of a thing and is classified to five types, M,F,E,K and S. These five types can be flexibly designed for the application area. We also defined Type matching rule. Type matching rule is used for selecting the knowledge from master Knowledge Network. There are two types of matching relations,Attracting Relation and Rejecting Relation[1].

Attraction Relation	Attracting degree $d_i$	
$M \oplus \gg F$	d1=0.5	
$F \oplus \gg E$	d <sub>2</sub> =0.5	
$E \oplus \gg K$	d <sub>3</sub> =0.5	
$K \oplus \gg S$	d <sub>4</sub> =0.5	
$S \oplus \gg M$	d <sub>5</sub> =0.5	
Rejecting Relation	Rejecting degree $d_i$	
$\begin{tabular}{lllllllllllllllllllllllllllllllllll$	Rejecting degree $d_i$ $d_1$ =-0.5	
$\begin{tabular}{lllllllllllllllllllllllllllllllllll$	Rejecting degree $d_i$ $d_1$ =-0.5 $d_2$ =-0.5	
$\begin{tabular}{ c c c c } \hline Rejecting Relation \\ \hline M \ominus \gg E \\ \hline E \ominus \gg S \\ \hline S \ominus \gg F \\ \hline \end{tabular}$	Rejecting degree $d_i$ $d_1$ =-0.5 $d_2$ =-0.5 $d_3$ =-0.5	
Rejecting Relation $M \ominus \gg E$ $E \ominus \gg S$ $S \ominus \gg F$ $F \ominus \gg K$	Rejecting degree $d_i$ $d_1$ =-0.5 $d_2$ =-0.5 $d_3$ =-0.5 $d_4$ =-0.5	

The matching rule 'M  $\oplus \gg (0.5)$  F' means that M type helps F type with attracting degree 0.5. The value  $d_s$  of 'M  $\oplus \gg (d_s)$  S' is derived from 'M  $\oplus \gg (0.5)$  F  $\oplus \gg (0.5)$  E  $\oplus \gg (0.5)$  K  $\oplus \gg (0.5)$  S'. The attracting degree of multiple relation is calculated by the following equation(2).

$$\mathbf{d}_{s} = \begin{cases} \prod_{i=1}^{n} (-1)^{n+1} \mathbf{d}_{i} & \text{if } Type_{i} \neq \mathsf{Type}_{j} \\ 1 & \text{otherwise} \end{cases}$$
(2)

If the value of  $d_s$  is positive, it is attracting relation. Otherwise, the minus value means rejecting relation.

#### 3. MEMORY RETENTION STRATEGY OF BALANCING NEUTRAL ENERGY POINT IN THE KNOWLEDGE NETWORK

#### 3.1 Self Energy and Neutral Energy Point

AS described in section 2,a knowledge node has its Self Energy. We define Self Energy as an internal energy which represents energy degree determining the activated state. Fig. 2 shows the gauge of energy which has a value between -1 and +1. The plus value means positive energy and the minus value means negative energy. The value 0 represents the balanced Neutral point. This value of Self Energy is continuously adjusted by activating state caused by entering Energy of input facts.





In the initial state, Self Energy,  $S_{E_i}$  of a knowledge node  $K_i$  has a value 0 on the balanced neutral energy point. But during repeated processing of Input facts, the value of Self Energy is continuously adjusted by activating state caused by entering Energy. If a input fact comes in and its type is matched with type of knowledge node, that knowledge node is selected and activated. Its Temporal Energy value, $T_{E_i}$  of knowledge node is changed and calculated by equation (4). If the type of input fact is not matched with the type of knowledge node which it finds,the node can't be selected and has no effects on the node.

$$T_i = S_{E_i} + I_{E_i} \tag{3}$$

where  $S_{E_i}$  is Self Energy value and  $I_{E_i}$  is the energy value of Input fact,  $I_i$ .

$$T_{E_i} = \frac{1 - exp(-T_i)}{1 + exp(-T_i)}$$
(4)

The temporal energy value is temporally made value and used for the knowledge retrieving process. Its temporal value effects on adjusting the value of Self Energy. Self Energy  $S_{E_i}$  is calculated by following equation (5).

$$S_{E_i} = f(S_{E_i}^{old} + (T_{E_i})^2)$$
(5)

$$f(x) = \begin{cases} x & \text{if } -1 <= x <= 1\\ 1 & \text{if } x > 1\\ -1 & \text{otherwise} \end{cases}$$
(6)

## 3.2 Memory cleaning by balancing Neutral Energy point : Forgetting

As the activating mechanism is progresses, the value of Self Energy is accumulated and getting higher. Then in the final state, the knowledge network arrives at the state which is easy to be activated by even tiny stimulus. For the efficient precise knowledge retrieval, this state not only cause inaccuracy but also may cause serious problems. For this reason, memory retention process by balancing the neutral energy point is needed.

To adjust the balancing Neutral Point, the system should calculate the total value of Self Energy of Knowledge nodes composing the knowledge network. Total Energy value,  $B_P$  is calculated by equation (6).

$$B_p = \frac{\sum_{i=1}^n S_{E_i}}{n} \tag{7}$$

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where n is the number of knowledge nodes.

For making the memory retention process, we designed the concept of Balancing Threshold, $\theta$ , as a retaining critical point. If Total Energy value is greater than or equal to the Balancing threshold, the knowledge nodes not frequently used are removed step by step according to the forgetting gauge, f, and the Self Energy value of survived knowledge nodes are reset as a value of the neutral point energy, zero.

Base on the Balancing Threshold, memory retaining process is performed by following algorithm.

#### **Algorithm 1 : Memory Retaining Mechanism**

 $\begin{array}{l} STEP1 \mbox{ input } \theta, {\rm f}; \\ STEP2 \mbox{ i=0}; \\ STEP3 \mbox{ Calculate } B_p \\ STEP4 \mbox{ If} ((B_P)^2 \ge \theta) \\ \mbox{ while}({\rm queue } != {\rm Empty}) \mbox{ do} \{ \mbox{ If } ({\rm f} == {\rm on}) \{ \\ \{ {\rm Remove the node; } \\ \mbox{ i++;} \} \\ \mbox{ Else} \{ \\ \mbox{ If } (S_{E_i} = 0) \\ \mbox{ Mark "Cleaning" flag; } \\ \mbox{ Else } S_{E_i} = 0; \\ \mbox{ i++;} \} \} \\ STEP5 : {\rm Stop.} \end{array}$ 

#### 4. EXPERIMENTS

We apply Memory retaining strategy to the example of virtual memory as following Fig.3 and tested with simple knowledge network. This knowledge network has 8 knowledge nodes and 7 associative relations connecting two nodes. The description about Type matching mechanism is abbreviated here because it is described in detail in the referred paper [1]. In this paper, the test for investigating the variation of Self Energy value inside the knowledge node was performed. We made an observation on activated state and the changes effected by 8 input facts which have values of Type and Energy. Fig.4, Fig.5 and Fig.6 show the result of changing Self Energy value according to the Balancing threshold. The cases of Balancing threshold = 0.3, Balancing threshold = 0.5and Balancing threshold = 0.7. were investigated respectively. Fig.7, Fig.8 and Fig.9 show the changing value of Internal Self Energy value in the graphic form. From the graphic form we can easily distinguish the fact that the smaller the value of Balancing threshold is, the shorter the time span of Balancing Neutral Energy point.

This memory retaining strategy can be applied for not only memory cleaning process but also used for controlling the activation level from the memory. And this system can be also applied to construct core brain like frame of Intelligent System.

#### **5. CONCLUSION**

In this paper, Memory Retention strategy by balancing Neutral Energy Point was proposed. Finding a clue



#### Fig. 3 Testing knowledge network

• D:WBPWaWa2WDebugWa2.exe	
Memory retention	
Balancing threshold:0.3	
0.5	
input energy 0.500000	
T= 0.244919 S=0.059985	
0.6	
input energy 0.600000	
T= 0.318514 S=0.161436	
0.7	
input energy 0.700000	
T= 0.405921 S=0.326209	
Balanced	
0.8	
input energy 0.800000	
T= 0.379949 S=0.144361	
0.3	
input energy 0.300000	
T= 0.218595 S=0.192145	
0.8	
input energy 0.800000	
T= 0.459023 S=0.402847	
Balanced	
0.6	
input energy 0.600000	
T= 0.291313 S=0.084863	
Press any key to continue_	

Fig. 4 Balancing threshold=0.3

from the brain functions of maintaining the memory, the memory is designed to be composed of knowledge networks with knowledge nodes. Knowledge node has three components of ID name, Type and Internal Energy. Neutral Energy point is also defined and Memory Retention and Retrieval strategy introducing the concept of Neutral Energy point is proposed. This strategy was applied to the virtual memory and experimented with sample testing data. As a result of experiments we could observed the successful changing process of Internal Self Energy by Type Matching mechanism and memory activation. This strategy can be applied to design and construct core brain like frame of Intelligent System.

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Fig. 5 Balancing threshold=0.5

61	D:WBPW	ła₩a2₩Debu	ıg₩a2.
Meno	ry rete	ntion	
Bala	ncing t	hreshold:0.	?
0.5			
inp	ut ener	gy 0.500000	
T= Ø	.244919	S=0.059985	
0.6			
inp	ut ener	gy 0.600000	
T= 0	.318514	S=0.161436	
0.7			
inp	ut ener	gy 0.700000	
T= Ø	.405921	S=0.326209	
0.8			
inp	ut ener	gy 0.800000	
T= Ø	.510277	S=0.586591	
0.3			
inp	ut ener	gy 0.300000	
T= Ø	.416372	S=0.759957	
Bala	nced		
0.8			
inp	ut ener	gy 0.800000	
T= 0	.379949	S=0.144361	
0.6			
inp	ut ener	gy 0.600000	
T= 0	.355898	S=0.271024	
0.8			
inp	ut ener	gy 0.800000	
T= 0	.489583	S=0.510716	
n			

Fig. 6 Balancing threshold=0.7

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Fig. 7 Balancing threshold=0.3



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Fig. 9 Balancing threshold=0.7