Memory Information Extension Model Using Adaptive Resonance Theory

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Abstract: The human being receives a new information from outside and the information shows gradual oblivion with time. But it remains in memory and isn't forgotten for a long time if the information is read several times over. For example, we assume that we memorize a telephone number when we listen and never remind we may forget it soon, but we commit to memory long time by repeating.

If the human being received new information with strong stimulus, it could remain in memory without recalling repeatedly. The moments of almost losing one's life in an accident or getting a stroke of luck are rarely forgiven.

The human being can keep memory for a long time in spite of the limit of memory for the mechanism mentioned above. In this paper, we will make a model explaining that mechanism using a neural network Adaptive Resonance Theory.

I. MEMORY OF HUMAN

A. Memory process of human

The cerebral cortex in brain of human deals with sensory informations received from outside environment and selects what to do in next time using the result. The process of cerebral cortex is as follows.

At first, Sensory organs receive sensory informations from the outside environment, then it is sent to the place of informations in the memory. Secondly, the sensory information is compared with the information in the memory, new information is memorized being separated from the information in the memory.

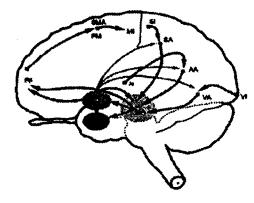


Figure 1. Signal flows of cerebral cortex

B. How to become long term memory?

Short term memory is the action that keeps the information received la last in the memory during only several seconds. There is a limit called memory span that is an amount of 7 words in short term memory, and the information is almost forgotten after about 18 seconds. Whereas when it is recalled repeatedly, it can be existed in the long term memory.

When the human being memorizes something, the properties that have made a strong impression on him tend to memorized hard.

In this paper, these two phenomena are assumed to be primary factors that keep the memory of human for a long time.

II. MODELING WITH NEURAL NETWORK

- A. Adaptive Resonance Theory(ART)[5][6][7]
- a) Characteristics of ART

ART adopts on-line learning and classifies the input data not being similar with the past information in memory as a new category. It is very similar with memory process of the human

being.

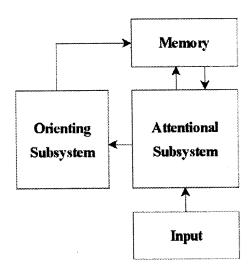


Figure 2. Structure of ART

b) ART algorithm

- To receive the input data.
- To search the most similar information with input data in the memory.
- To estimate how much those are similar and weather those are similar or not.
- To update the memory to more similar with the input if those are similar.
- To memorize the input in a new memory space if those are not similar.
- c) Problems of general ART
- New informations are always memorized into the long term memory directly.
- The information memorized once is not forgotten forever.

These problems restrain us from representing the proposed algorithm with ART. For the purpose of this paper, we modified ART.

B. Modified ART

The modified ART algorithm is as follows.

- To name the firstly memorized information in a new category as short term memory.
- To rename it as long term memory when the

- information named as short term memory is repeatedly received.
- If short term memories are not recalled, then the informations are forgotten.
- To name the new information with strong stimulus as long term memory directly.

III. SIMULATION

A. Input data

a) Using sensory information

When the human being recognizes something, they judge it using the sense of sight, touch and so on. This ability is the function of cerebral cortex. The sensory cortex in cerebral cortex receives information from the sense organs, The combination cortex deduces and judges with it(Figure 3). To model the human being's function memorizing something, it is held that using informations from sensory organs in Table 1 and the informations are adjusted to using as inputs of ART in Table 2.

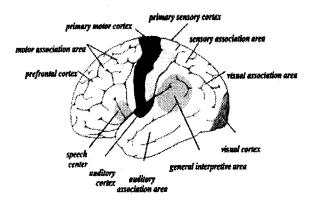


Figure 3. Definition of cerebral cortex

Table 1. Examples of Sensory Input

Color: The colors are represented in RGB, each element is from 0 to 255.

Shape: In this case, only rectangle and circle were considered as input.

Sound: Amount of sound the object makes when it is knocked.

Sound, friction and compliance inputs are valued from 0 to 100 by experimentor's impression.

				Visual	Sound	Touch				
[Color			Shape		Valuena				
	R	G	В	Rectangle	Circle	(cm³)	(Knock)	Friction	Compliance	
Apple	245	61	88	х	0	523.6	35	71	50	
Basketball	248	105	69	х	0	14137.2	57	23	79	
Book	29	72	220	0	х	4200	78	50	19	

Input data:[.96 .24										
Normalized input:	•	9.1391	8.2828	0	8.5794	0.0110	0.2028	8.4114	0.2897	
State and output:	Add a new i									
Hemory 1 (STH) :	0.5562	9.1391	0.2828	0	8.5794	0.0110	0.2928	8.4114	0.2897	5.0000
Input data:[.97 .41						B 0040	0.0045	A 4007		
Hormalized input:		3.2295	8.1452	0	0.5377	B.2818	0.3 0 65	0.1237	9.4248	
State and output:	Add a new o			_					0.0007	
Hemory 1 (STM) :		9.1391	0.2028	0	0.5794	0.0110	0.2028	8.4114	9.2897	4.0000
Memory 2 (STM) :	8.5216	0.2205	0.1452	6	0.5377	9.2818	0.3065	8.1237	0.4248	5.0000
		F4 0F	70 01							
Input data:[.96 .48		.50 .25 . 8.2165	8.1515	8	8.5411	8.2814	9.3939	0.1353	8.4221	
Hormalized input:	•			U	W.3411	0.2014	0.3030	9.1000	8.4221	
State and output:	Resonant wi		8.2 0 28	8	0.5794	8.8110	0.2028	8.4114	0.2897	3.8888
Memory 1 (STM) :		9.1391		8	0.5381	8.2817	9.3962	0.1248	0.4245	10.0000
Hemory 2 (STH) :	0.5214	0.2281	8.1458	U	W.5381	0.2617	9.3002	U. 1240	W.4245	. 0. 0000
Input data:[.99 .44	22 6 00 1	E EE 99	77 61							
Normalized input:		,, ,,, B.2369	8.1185	8	9.5331	9.2962	8.2962	0.1185	9.4146	
State and output:	Resonant w			•	•	012702	0.2702	011103	0.4140	
Memoru 1 (STM) :		0.1391	8.2020		0.5794	9.0110	9.2028	8.4114	0.2897	2.0000
Memory 2 (LTM) :		8.2218	0.1431	8	0.5376	0.2832	0.3052	0.1242	9.4236	15.0000
nemory 2 (LIN) .	8.3220	8.2210	V. 1701		0.5070	0.2002	8.0472	0.1272	0.4200	
Input data:[.9 .4 .2	0.055	2 7 81			-					
Mormalized input:		8.2369	8.1185	8	8.5331	8.2962	9.2962	8.1185	9.4146	
State and output:	Resonant w			-			••			
Memory 1 (STM) :		0.1391	8.2028	0	0.5794	0.0110	0.2828	0.4114	9.2897	1.0000
Memory 2 (LTM) :		9.2233	8.1496	Ā	0.5372	0.2845	9.3843	8.1236	0.4227	15.0000
				-			•••			
Input data:[.95 .45	.25 .85 1 .9	55 .55 .25	.75 .051							
Mormalized input:		8.2448	8.1356	8.8271	8.5423	9.2983	9.2983	9.1356	9.4867	
State and output:	Resonant w									
Memory 1 (EMPTY):	8	e .		8			9	0	8	
Memory 2 (LTM) :	8.5229	8.2254	0.1481	8.8027	0.5378	8.2859	0.3037	8.1248	8.4212	15.0000
(2111,	••									
Input data:[.11 .28	.86 1 8 .150	6 .78 .5 .	.19 1]							
Hormalized input:		8.1689	8.5187	8.6931	8	8.9941	9.4784	8.3016	9.1146	1
State and output:	Add a new a	memory 3.								
Hemory 1 (EMPTY):	8	0	e	9			9	9	9	0
Hemory 2 (LTH) :	0.5229	0.2254	9.1491	0.0027	8.5378	9.2859	0.3037	0.1248	9.4212	15.0000
Hemory 3 (LTM) :	0.0663	0.1689	0.5187	0.6831		0.0941	0.4764	0.3016	0.1146	15.0000
Input data:[.11 .28	.86 1 8 .15	6.78.5	.19 8]							1
Mormalized input:	0.0663	0.1689	0.5187	6.6831	•	8.0941	0.4784	8.3816	8.1146	
State and output:	Resonant w	ith memory	3.							
Memory 1 (EMPTY):	•	8	0	. 9			8	9	0	8
Hemory 2 (LTH) :	8.5229	8.2254	8.1481	0.0027	0.5378	0.2859	0.3037	8.1248	0.4212	15.0 000
Memory 3 (LTM) :	8.0663	0.1689	8.5187	0.6931	8 -	9.0941	0.4704	0.3916	8.1146	15.0000
Input data:[.1 .2 .8					_		a b	0.0405		
Hormalized input:		0.1278	0.5111	0.6389	8	0.8639	8.4472	8.3194	8.0639	
State and output:	Resonant w	-		_	_	_	_	-	_	_
Hemory 1 (EMPTY):			0	0	0	9	9	0 4050	0 6040	45 0000
Memory 2 (LTM) :		0.2254	6.1401	0.0027	0.5378	0.2859	8.3837	8.1248	0.4212	15.0008
Hemory 3 (LTH) :	0.9661	0.1648	0.5181	8.6969		0.8911	8.4683	8.3835	9.1896	15.0000

Figure 4. Simulation results

The last column of input data is emotion input. That is separated from sensory informations. The simulator normalize the input data first. The upper side of output is normalized input and the lower side of output is memory. Output of ART is the added new line or the resonated line. The last column of memory is memory factor. When a memory is recalled, The memory factor is increased by 5 but when not recalled, it is decreased by 1. The range of memory factor is from 0 to 15. When the factor is equal to 0, the memory is erased and when it is equal to 15, it means long term memory and it doesn't decrease. When the emotion input is equal to 1, it means a strong impression and it becomes long term memory directly.

				Visual		Touch			
	(Color		Shape					l 1
	R	G	В	Rectangle	Circle	Volume	(MINOCK)	Friction	Compliance
Apple	0.96	0.24	0.35	0	1	0.019	0.35	0.71	0.50
Basketball	0.97	0.41	0.27	0	1	0.524	0.57	0.23	0.79
Book	0.11	0.28	0.86	1	0	0.156	0.78	0.50	0.19

Table 2. Examples of Sensory Input(adjusted)
Every values are adjusted to 1 or less.
Volumes are expressed at the ratio to 30*30*30(CM³)

b) Effects of emotions

When the input data with strong stimulus is memorized in long term memory directly, we will receive the information of emotions to know weather the stimulus is strong or not. We assume that the stimulus is strong if an emotion data is high.

B. Results

Short term memory was erased when it is not received repeatedly, memory recalled repeatedly became long term memory, long term memories are not forgotten, and the input with strong stimulus became a long term memory at once.

IV. CONCLUSION

This paper introduces the model for the process that the human being keeps information in the long term memory using ART that is modified and simulated through program. To realize the system, technologies that can measure sensory information and emotions are required.

V. ACKNOWLEDGEMENT

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