Simile Understanding System Using Associative Concept Dictionary and Pulsed Neural Network

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Abstract

When considering natural language processing by a computer, it is necessary to design a large-scale knowledge base about concepts. In this study, at first we have constructed such a knowledge base as a brain memory model (BMM), based on the associative concept dictionary and a pulsed neural network. BMM is not only for a static structure of concepts but also for dynamic behaviors such as associating or restructuring, which is expected for both cognitive simulations and applications for computer systems. Thus we considered the application of BMM, constructing the simile understanding system (SUS) which transfers a typical simile expression into a simple simile-understood expression. We mentioned to some of properties about a simile expression, in order to improve the performance of SUS. As the third step of this study, we made a questionnaire on www for the purpose of investigating human simile understanding and compared the outputs of the system with the results of this questionnaire. And we finally concluded that our system is useful for simile understanding.

Key Words: concept structure, simile understanding, associative concept dictionary, neural network

1. Introduction

Natural language processing is one of the most important functions for computer technology now. It is expected to be applied to a new type of OS, robot technologies and so on. A knowledge base for natural language processing is very difficult to construct, which is absolutely necessary for the system. Thus we have not yet found a computer system which could understand the input texts satisfactorily.

On the other hand, human beings have such a database in their brains as a memory structure, which is often modeled as a concept dictionary. It consists of a number of concepts and they are connected with each other in a complex manner. Human beings can easily understand natural languages by using language faculty and language memory unconsciously.

Referring to such a human superior mechanism and constructing its model with cognitive analysis is one of the valuable ways to the realization of natural language processing by a computer. This study is to suggest the model about concepts and their structure in a human brain and to consider its application for simile understanding system, as a part of a study for natural language processing.

2. Purpose and Backgrounds

2.1 Outline of the Study

This study consists of three steps shown below.

First, we have designed a model for a typical human memory structure, based on the associative concept dictionary[11] for its knowledge-base and a pulsed neural network[4][7] for its process algorithm. We named this model as "Brain Memory Model (BMM)". BMM is not only for a static model expressing a concept structure but also for a dynamic model dealing with associating or restructuring of memories. It is available for both simulations of human memory activities and some applications on computer.

Secondly, as an application of BMM, a computer system is constructed that understands metaphor expressions, especially simile expressions. A goal of this system is to transfer a typical simile expression such as "*The T seems just like S*" into a simile-understood expression "*The T is so U*", where T is a simple word called "a target concept", S is "a source concept"[10], and U is a word showing a feature of T. T and S are both defined as nouns while U is generally an adjective. Users input T and S into the system and get U as a result of an analysis by the system. Such a system has been constructed based on BMM and named as "Simile Understanding System (SUS)".

And in the third step of this study we have evaluated SUS, by means of comparing its output with those by subjects using a questionnaire.

2.2 Contributions

We believe that BMM has at least two probabilities for contributions. One is the probability to obtain the clue for solution about human intellectual activities, such as associating, learning or understanding, through some simulations with BMM. Another probability is the application for the computer system, especially for natural language processing. In this study, we would mention to the latter probability of BMM mainly, with constructing SUS.

The contribution of SUS is to help the computer with understanding natural language. One of the important problems is that human beings use a various kind of expressions in daily conversations. When considering to treat these whole expressions with a computer, it is a valuable way to change each complicated expression into simpler at first. SUS transfers a simile expression into a simple one, playing the role as the preprocessor before semantic analysis, which makes it much easier to understand a simile expression with a computer.

2.3 Backgrounds and Features

BMM is a kind of model for human memory structure, especially for a concept structure. The structure is similar to the semantic network[3]. It expresses a memory structure with a number of concepts and links among them to show their relations. The difference of these two is that the semantic network is a static model only for a structure of concepts, while BMM is a dynamic model dealing with some brain behaviors.

BAM (bi-directional associative memory)[2] and MAM (multi-directional associative memory)[5] are also typical dynamic models for human memory system. They are the models suggested in computer science but no cognitive data are used in their structures.

BMM is designed based on both the associative concept dictionary and a neural network, which takes a large advantage of cognitive data from the former as well as inheriting neuron dynamics from the latter, realizing a multidirectional multipurpose model.

SUS is an application of BMM, which understands a simile expression explained above. We could find some other simile or metaphor understanding systems suggested before, with introducing a parameter "saliency"[10] or using some properties of concepts expressed as a polygon on a radar chart[9]. These methods are valuable but geometrical methods, designed without mentioning to human mechanism.

On the other hand, SUS is based on BMM, where a human memory model is applied to simile understanding. We suggest a new approach through the construction of SUS, which is more cognitive solution for simile understanding problem.

3. Design for Brain Memory Model

3.1 Implementation

As mentioned in above sections, Brain Memory Model (BMM) is constructed based on data in the associative concept dictionary and architecture of a pulsed neural network.

The associative concept dictionary[11] is a kind of a large scale database about concepts human beings basically have in their memory, constructed through cognitive experiments. It contains currently about 1,000 concepts for stimulus words and about 90,000 concepts for associated words for Japanese only, and relational information among each concept with quantitative distance values. In the associative concept dictionary, concepts are treated for not only noun but also verb, adjective and so on, thus we consider a various kind of part of speeches as a concept in this study.

In a design of BMM, these data are transplanted into architecture of a pulsed neural network. In detail, concepts in the associative concept dictionary are transplanted into neurons in the pulsed neural network for one-on-one, while the distance between two concepts is transplanted into a synapse weight between corresponded neurons (See Fig.1).

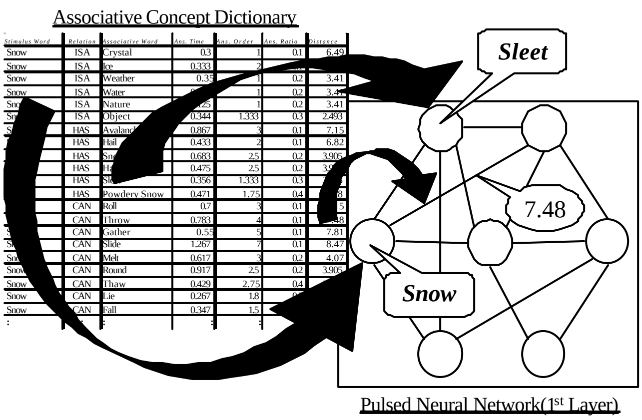

Fig.1: Plantation of Data

In transplanting concepts into neurons, we mentioned to a part of speech of concepts and separated them in each layers of a neural network. We prepared architecture of a neural network for three layers, transplanting noun concepts into the first layer, verb into the second layer and adjective into the third layer.

On the other hand, we adopted a way of conversion from a distance in the associative concept dictionary into a synapse weight in a neural network (See Eq.1)

$$w_{ij} \;=\; \omega / d_{ij} \;*\; \sum_{k=1}^{k\,\max} w_{ik}{}^{2})^{1/2} \qquad (1)$$

where w_{ij} is a synapse weight from neuron j to neuron i, d_{ij} is a distance from concept j to concept i, and ω is a constant adjusting the order of synapse weights, usually defined as ω=0.1. From this equation, the shorter the distance between concepts is, the stronger the synapse weight between their neurons set.

As mentioned above, one concept is expressed by one neuron in BMM. It follows the physiological hypothesis known as the "grandmother cell[1]", which is not accepted nowadays as the real coding in a human brain[6]. It seems that the grand mother cell model is not appropriate as a brain model, but we could solve this dilemma considering that a neuron in BMM corresponds not to a single neuron but to a certain firing pattern organized with several neurons in a brain. BMM is, therefore, a model not for the detailed structure of neurons but for the concepts and their relations, where the accuracy is enough for the grand mother cell.

3.2 Linkage Module

One of the functions BMM supports is adding a new relation between two concepts by linking them with a new synapse. It means that when the model finds an indirect relation between two concepts, it would connect them with a directly link. It works for each concept if and only if related through another concept indirectly in a certain area. In this study we named this function “linkage module”.

In the associative concept dictionary, most associative words are related with nothing but only their each stimulus word, that is much poor comparing with human brain. The linkage module plays the role to construct relations among their associative words, enriching the network of BMM and extends its availability.

However, constructing too many relations by the linkage module might be a cause of saturation of the network. A saturated network does not make any sense as the memory structure. Therefore, we always need to consider under each situation whether the linkage module should be applied or not, in order to keep the best performance of BMM.

3.3 Functions of Brain Memory Model

We have constructed Brain Memory Model (BMM) on a computer by JAVA programming, which supports some functions as shown below:

(1) **Associating process function:** When we input a first concept into BMM, it starts the associating process that searches an associated concept one after another. This function is performed by using a chain dynamics of firing of a neural network.

(2) **Searching a common concept function:** It could also search and list concepts which is commonly related with both of two concepts. This is a developed version of function (1), running an associative process with inputting two concepts.

(3) **Adding new relations function:** BMM can construct a new relation between two concepts if they are connected indirectly. This function is performed by the linkage module explained above.

4. Design for Simile Understanding System

4.1 Algorithm

In this section we would explain about Simile Understanding System (SUS) constructed as an application of BMM. This system transfers a simile expression "*The T seems just like S*" into a simile-understood expression "*The T is so U*". SUS solves this problem by means of searching a common concept U between T and S, which has been explained for the second function of BMM.

Let a user input a simile expression "*The skin seems just like snow*" into SUS through GUI module. The system activates BMM and input “*skin*” and “*snow*” into there. It makes the neuron "*skin*" and the neuron "*snow*" in BMM excited enough for fire, and starts a chain dynamics in BMM. It affects other linked neurons and increases their membrane potentials. In this case, fire of the neuron "*snow*" propagates to the neuron "*white*" and "*cold*", while fire of the neuron "*skin*" propagates to the neuron "*white*", "*beautiful*" and "*smooth*". Note that the neuron "*white*" is related with "*snow*" and "*skin*", excited by both of two neurons and its membrane potential is also increased in two times. As a result, the neuron "*white*" is most strongly excited in BMM and the system finally outputs the simile-understood expression "*The skin is so white*" on GUI module (See Fig.2).

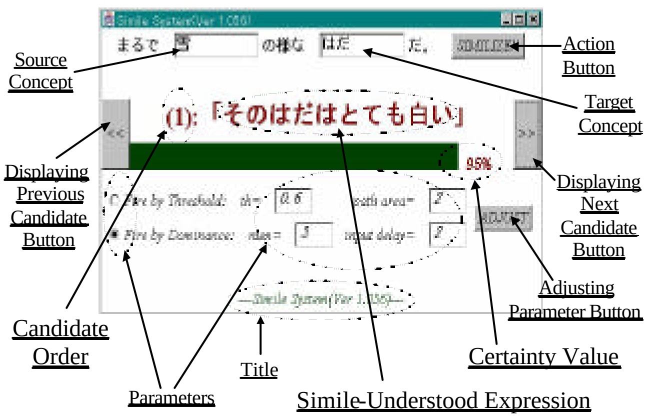

Fig.2: GUI Image of SUS

During the process of searching a common concept U, the system searches only on the third layer for adjectives and other layers are knocked down. Also, there might be a case that two or more neurons are fired simultaneously in BMM as a result of the searching and the system outputs several candidates of

U, such as U_1, U_2, U_3, etc. The number of these candidates is adjustable by changing the value of threshold θ.

4.2 Calculation of the Certainty

SUS calculates the value of "certainty" for each candidate of U. In this study this value is defined as the scale explaining how the system itself is confident for the candidate. It depend on a membrane potential for each firing neuron (See Eq.2)

$$\begin{cases} c_i = [\, f(\gamma_2 * (h_i(t_F) - \gamma_1)) * 100 \,] \\ f(x) = 1 / (1 + \exp(-x)) \end{cases} \quad (2)$$

where c_i is a percent value of the certainty and $h_i(t_F)$ is a membrane potential of neuron i at firing time t_F[4]. γ_1, γ_2 are constants, usually set as γ_1=0.5 and γ_2=20.0. $f(x)$ is a sigmoid function, which is used just only as the means for normalization of c_i here.

From this equation, we could find that the higher a membrane potential of the candidate is, the more confidence the system has for it. After a calculation of the certainty, the system decides the candidate order and sorts them in descending order.

4.3 Difference between Source/Target Concept

In general, a target concept and a source concept are not exchangeable with each other. For instance, the simile expression "*The person seems just like a devil*" quite differs from the other expression "*The devil seems just like a person*", interpreted as "*terrible*" for the former while the "*kind*" or "*wise*" for the latter, in contrast. These interpretations are both related with their source concepts rather than their target concepts, thus we assumed that a source concept is more effective than a target concept in simile understanding. According to this hypothesis, we have strengthened the effect of a source concept in the system, by means of delaying the firing of a source concept neuron than the firing of a target concept neuron in BMM. The architecture of BMM follows a pulsed neural network, which has the property that an older fire of a neuron is less effective than a newer one[4][7]. As a result, the later firing of a source concept has more effect than the earlier firing of a target concept, realizing the best equilibrium of these two effects for simile understanding.

4.4 Applying Linkage Module

In order to improve the performance of SUS, we applied the linkage module to the target concept T.

As mentioned above, the linkage module adds new relations among concepts and enriches them. As a result, the simile expression "*The boss seems just like a devil*" could become interpreted as "*terrible*" just like as "*The person seems just like a devil*", where a target concept "*boss*" had been enriched by the linkage module and finally had the equivalent information to the concept "*person*".

On the other hand, we did not apply the linkage module to the source concept S, for the purpose of avoiding a risk of saturation of the network. This problem is that the simile expression "*The person seems just like Satan*" and "*The person seems just like an imp*" might be the same interpretation, because of having the equivalent relations by applying the linkage module. We considered that this problem is more critical to a source concept rather than a target concept, thus decided to apply it only for a target concept.

4.5 Results

We have constructed SUS by JAVA, and experimented with some tasks for simile understanding. Here we show the tasks used in the experiment and the results SUS output for each task (See Table1). In the table S and T donate a source concept and a target concept input by users, while U_1 is the first candidate SUS output, with a highest certainty c_1. Thus it shows that, for instance, the input of Task1 was "*The skin seems just like snow*" and SUS output "*The skin is so white*" as the most reliable candidate for it with the certainty value 95%.

Table1: 12 Tasks and Outputs of SUS

	S	T	U_1	c_1(%)
Task 1	*Snow*	*Skin*	*White*	95
Task 2	*Snow*	*Mind*	*Cold*	95
Task 3	*Devil*	*Person*	*Fearful*	95
Task 4	*Person*	*Devil*	*Wise*	80
Task 5	*Friend*	*Drink*	*Reliable*	99
Task 6	*Lake*	*Eye*	*Calm*	99
Task 7	*Mirror*	*Sky*	*Fragile*	93
Task 8	*Stone*	*Character*	*Solid*	99
Task 9	*Arrow*	*Time*	*Short*	81
Task10	*Star*	*Sand*	*Beautiful*	14
Task11	*Needle*	*Words*	*Sharp*	88
Task12	*Ice*	*Smile*	*Cold*	50

5. Evaluation of Simile Understanding System

5.1 Human Simile Understanding

To evaluate Simile Understanding System (SUS), we investigated the difference of the outputs between SUS and human beings. At first, we used a questionnaire to investigate simile understanding by human beings. The subjects judged about each candidate how they were appropriate as the interpretation for its simile expression, marking a score on a scale of one to ten. 12 simile expressions and 3 candidates for each expression were used for the questionnaire, which is equivalent to inputs and outputs in tasks for the experiment of SUS (See Table1). This questionnaire was done on WWW in 4 days, and we got 60 samples of data as a result.

5.2 Results and Discussion

A typical result of the investigation is shown below (See Fig.3). It is a frequency distribution for each candidate in Task1:"*The skin seems just like snow*", where m_1, m_2 and m_3 are the mean of scores for each candidate. The number with a bracket written after the candidate is a value of the certainty.

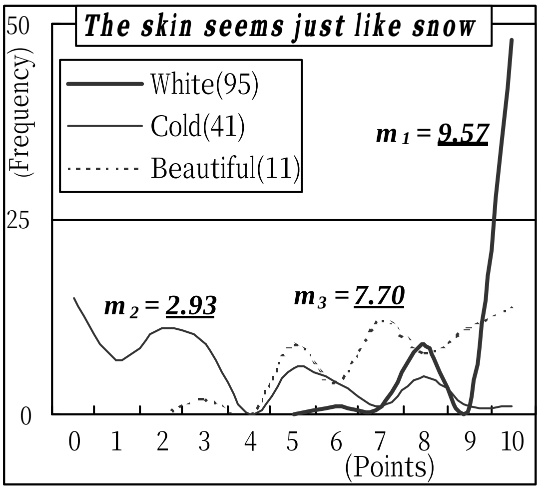

Fig.3: frequency distribution for Task1

From this figure, the score of the first candidate "*white*" is so high, while the score of the second candidate "*cold*" and the third candidate "*beautiful*" are not so high. This tendency is obtained in almost all 12 tasks, and we concluded that the candidate with a better certainty value is also marked with a higher score in the questionnaire. This means that SUS can output the best candidate for simile understanding as the first candidate, with an appropriate calculation of the certainty value. Besides, we obtained totally high scores in the questionnaire, with 8 cases from 12 tasks with the mean of scores for the first candidate m_1 exceeding 6.0, including 5 cases exceeding 8.0.

From these results, we finally concluded that the outputs of SUS are not against the general feeling of human beings, and it could be available for basic problems of simile understanding, especially as the preprocessor before the semantic analysis.

6. Conclusion

In this study, we have constructed BMM, using data in the associative concept dictionary and architecture of a pulsed neural network. We have added the linkage module to BMM, which searches an indirect relation between any two concepts and relates them with each other directly. Secondly, we have considered to apply this model to the problem of simile understanding, and constructed SUS. It could transfer a simile expression into a simile-understood expression, with calculating a value of the certainty. And we have analyzed this system, comparing its outputs with general simile understanding of human beings, which is investigated through the questionnaire on www.

There might be some problems left for future works. First, we should argue the justification of the bias for a source concept, or the property of the linkage module applying in SUS. Also, we should check the accuracy for simile understanding, especially a value of the certainty, analyzing much more tasks or testing other kinds of expressions. As to BMM, we should improve it adding more available data or functions. Especially, we would like to realize a function for restructuring of the memory structure, which needs another module decreasing and deleting unnecessary relations as well as the linkage module which adds new relations. We would like to apply this BMM not only to simile understanding but also to various problems, to consider its potential. Finally, we would like to keep improving BMM and construct a complete model, explaining the whole memory structure in the brain and realizing simulations of intellectual activities, that would be called the "real" brain memory model in the future.

References

[1] Barlow,H.B., "Single units and sensation: a doctrine for perceptual psychology?", Perception, 1, 371-394, 1972.

[2] B.Kosko, "Bidirectional associative memories", IEEE Trans. Syst., Man, and Cybern., SMC-18, 1, 49-60, 1988.

[3] Collins,A.M. & Quillian,M.R., "Retrieval time from semantic memory", Journal of Verbal Learning and Verbal Behavior, 8, 240-247, 1969.

[4] E.Domany, J.L.van Hemmen, K.Schulten, "Models of Neural Networks II --- Temporal Aspects of Coding and Information Processing in Biological Systems", Springer-Verlag, 1994.

[5] M.Hagiwara, "Multidirectional associative memory", Intt. Joint Conf. on Neural Networks, I, 3-6, 1990.

[6] Palm,G., "Cell assemblies, coherence, and corticohippocampal interplay", Hippocampus, 3, 219-226, 1993.

[7] Wolfgang Maass and Christohper M.Bishop, "Pulsed Neural Networks", MIT Press, 1999.

[8] S.Ishizaki, "Natural Language Processing", Shokodo, 1995.

[9] Y.Imai, "A Study for Metaphor Calculating Model Based on Language Cognition of Human Beings", Keio University Media and Governance Doctor Thesis, 2000.

[10] M.Iwayama, K.Tokunaga, H.Tanaka, "The Role of Salience in Understanding Metaphors", Journal of Japanese Society for Artificial Intelligence, Vol.6, No.5, 674-681, 1991.

[11] J.Okamoto, S.Ishizaki, "Quantification of Concept Space in the Concept Dictionary", ICCS/JCSS99, 748-751, 1999.

[12] M.Ogiwara, "Neuron, Fuzzy and Genetic Algorithm", Sangyotosho, 1994.

[13] N.Osaka, "Brain and Working Memory", Kyoto University Academic Press, 2000.

[14] T.Kusumi, "Processing Metaphors and their Semantic Structures", Kazamashobo, 1995.

[15] T.Koyadzu, "Basic Psychology --- 4 Memory", Tokyo University Press, 1982.

[16] N.Babaguchi, S.Yamada, "Basis of AI", Shokodo, 1999.

[17] Y.Moridaira, "An Extra Number of Mathematical Science: Memory --- Approaches to the Profound Structure of Information Processing", Science Corporation, 1983.