2003 International Symposium on Advanced Intelligent Systems
September 25-28, 2003, Jeju, Korea

EXPERT KNOWLEDGE GATING MECHANISM IN THE HIERARCHICAL MODULAR SYSTEM

Jeong-Yon Shim

Gs. of Computer Science
KangNam University
GuGal Ri, KiHeung Eup,YongIn Si,
KyeongKi Do, Korea
e-mail: maria4927@hanmail.net

You-Sik Hong

Dept. of Computer Science, SangJi Univ.
WonJu, KangWon Do, Korea
e-mail:yshong@sangji.ac.kr

ABSTRACT

For the purpose of building the more efficient knowledge learning system, it is very important to make a good structure of the knowledge system first of all. The well designed knowledge system can make the stored knowledge to be easily accessed for knowledge acquisition and extraction. Expert knowledge can also play a good role for controlling. Accordingly, in this paper we propose the Hierarchical modular system with expert knowledge gating mechanism. This system consists of the mechanisms for knowledge acquisition, constructing the associative memory, knowledge inference and extraction according to the expert knowledge gating mechanism. We applied this system to the medical diagnostic area for classifying Virus(coxackie virus, echovirus ,cold), Rhinitis(Nonallergic ,allergic) and tested with symptom data

1. INTRODUCTION

The function of human brain is known to be very complex and mysterious. But it is guessed that the patterns of stored knowledge inside brain may form the hierarchical structure according to their associative relations. It is proved that we can easily retrieve the stored data if we memorize the information according to the associative conceptual form of 'mind map'. Expert knowledge can also play a good role for controlling.In order to build the more intelligent knowledge base system, it is necessary to introduce these concepts to the computer aided knowledge base system.

Many studies of modular system have been made for solving the problem of several different domains recently. However, the structures of these models are very simple and can not provide the combined way for covering the various functions of intelligent system. For the efficient system, it is necessary to build the more intelligent combined way.

In this paper we propose Hierarchical modular system with expert knowledge gating mechanism. This system has the mechanisms of knowledge acquisition, constructing the associative memory and knowledge inference-extraction by expert control. We applied this system to the medical area and tested with symptoms for the medical diagnosis.

2. HIERARCHICAL MODULAR SYSTEM

For making the intelligent system we designed the Hierarchical modular system. Its structure has the modular system which can process the data of different domains. And it has also a hierarchical functional level which perform data reaction, knowledge acquisition, Inference and extraction according to the associative relations. This system has the hierarchical structure as shown in the following Figure 1. It consists of three parts, namely Input-Reaction layer, Pattern Learning layer and Associative knowledge inference layer[1].

If the data come in to Input-Reaction layer, they are filtered according to the category and propagated to Pattern Learning layer for the learning process. The output nodes from Pattern Learning layer are connected to each other by their associations. These connections of nodes contribute to the Inference-Extraction mechanism.

3. MEMORY CONSTRUCTION BY KNOWLEDGE ACQUISITION MECHANISM

In this system memory is constructed by the knowledge acquisition mechanism. This knowledge acquisition mechanism has three steps.

The first step is to classify the training data according to the different categories in the Input-Reaction layer. Input-Reaction layer is used for the input interface in the Bottom-up approach of knowledge acquisition mechanism. When the mixed data come in to this layer, data are filtered by

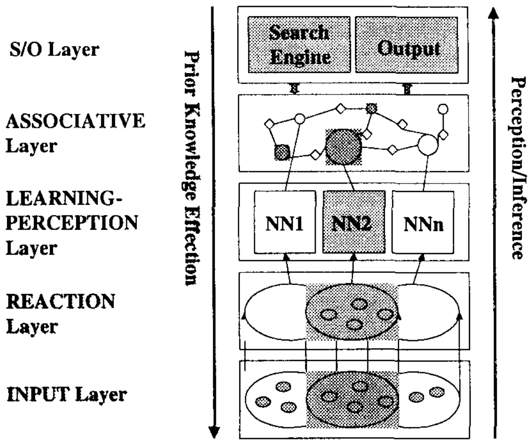

Figure 1: System overview of Hierarchical modular system

the filtering function. Some KLN are selected and fired for learning.

The second step is to perform the learning mechanism in the Pattern learning layer. KLNs(Knowledge Learning Nets) in the Pattern learning layer are in charge of learing function. KLN(C_i) consists of three layered feedforward neural network. This structure represents IF conditional part -THEN consequent part rule. Learning mechanism is performed by BP algorithm[5].

The third step is to construct the associative relations in Associative knowledge Inference layer. One KLN belongs to a certain class and is connected to the node in Associative Knowledge Inference Layer vertically. The outputs are transformed to the node in this layer. The nodes in Associative Knowledge Inference layer are connected each other according to the associative relations horizontally. In the knowledge extraction mechanism, the related facts are retrieved using these relations.

The representation of horizontal relations

If there are the associative relations represented in the relational graph as shown in Figure 2, these relations can be transformed to Associative Matrix(AM) as shown in Figure 3. We represent the associative relations in both linguistic terms as TRANSFER-TO, AFFECT, IS-A, MADE-OF, NOT, SELF and the numerical terms.

TRANSFORM-TO : transform in time
AFFECT : partial transform
IS-A : generalization
MADE-OF :component

In the relational graph, these linguistic terms are represented above arrow sign The minus sign means the opposite directional relation as -TRANSFORM-TO. These terms can be transformed to the numerical associations that are used in knowledge extraction step.

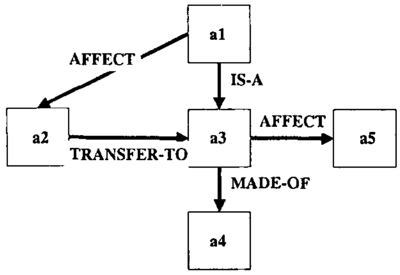

Figure 2: Relational graph

	a1	a2	a3	a4	a5
a1	SELF(R11)	IS-A(R12)	IS-A(R13)	NOT(R14)	NOT(R15)
a2	-IS-A(R21)	SELF(R22)	TRANSFER-TO(R23)	NOT(R24)	NOT(R25)
a3	-IS-A(R31)	-TRANSFER-TO(R32)	SELF(R33)	MADE-OF(R34)	AFFECT(R35)
a4	NOT(R41)	NOT(R42)	MADE-OF(R43)	SELF(R44)	NOT(R45)
a5	NOT(R51)	NOT(R52)	-AFFECT(R53)	NOT(R54)	SELF(R55)

Figure 3: Associative Matrix(AM)

We define the degree of relation between a_i and a_j as Numerical associative factor, R_{ij}. R_{ij} is calculated by equation (1).

$A = [\ a_{ij}\ ]$

$$a_{ij} = P(a_i|a_j)D \tag{1}$$

where D is the direction arrow, $D = 1, -1$, $i = 1, \ldots, n$, $j = 1, \ldots, n$.

Accordingly, the relations of AM can be converted to the following numerical terms.

$$A = \begin{bmatrix} 1.0 & 1.0 & 1.0 & 0.0 & 0.0 \\ -1.0 & 1.0 & 0.7 & 0.0 & 0.0 \\ -1.0 & 0.7 & 1.0 & 0.6 & 0.3 \\ 0.0 & 0.0 & -0.6 & 1.0 & 0.0 \\ 0.0 & 0.0 & -0.3 & 0.0 & 1.0 \end{bmatrix}$$

From this Associative Matrix(AM), we can extract the inferential path which can be used in knowledge extraction step. This Associative Matrix can be represented by the following linguistic terms.

a_1 IS-A(1.0) a_2 TRANSFER-TO(0.7) a_3 MADE-OF(0.6) a_4 ...(1)
a_1 IS-A (1.0) a_2 TRANSFER-TO(0.7) a_3 MADE-OF(0.6) a_5
a_1 IS-A(1.0) a_3 MADE-OF(0.6) a_4
a_1 IS-A(1.0) a_3 MADE-OF(0.6) a_5

4. KNOWLEDGE EXTRACTION USING THE EXPERT KNOWLEDGE GATING MECHANISM

In the previous section the process of constructing the associative relations was described. These relations are automatically made by the system. But for building the efficient and correct system, the expert knowledge is necessary.

The representation of horizontal relations

In this system we design the expert knowledge gating mechanism adding Expert Gating Matrix(EGM) to Associative Matrix. Expert Gating Matrix reflects the expert knowledge to the strength of associative relations. Expert can put the signal to the relations and control the strength of the relation using EGM. EGM is initialized by element value 1.0. If there is a expert signal, the element values are changed.

$E = [\ e_{ij}\ ]$

$$E = \begin{bmatrix} 1.0 & 1.0 & 1.0 & 1.0 & 1.0 \\ 1.0 & 1.0 & 1.0 & 1.0 & 1.0 \\ 1.0 & 1.0 & 1.0 & 1.0 & 1.0 \\ 1.0 & 1.0 & 1.0 & 1.0 & 1.0 \\ 1.0 & 1.0 & 1.0 & 1.0 & 1.0 \end{bmatrix}$$

The final associative Matrix(FAM),R, can be gained by equation (2).

$R = [\ r_{ij}\ ]$

$$r_{ij} = a_{ij} * e_{ij} \tag{2}$$

4.1. The mechanism for Knowledge Inference-Extraction

In this system, Knowledge extraction mechanism can be processed by following Alg. 1.

Alg.1 Associative extraction algorithm

Step 1: Search the associated nodes in the row of the activated node in FAM.

Step 2: IF((not found) AND (found the initial activated node))
Goto Step 3.
ELSE
Output the found fact.
Add the found fact to the list of inference path.
Goto Step 1

Step3: STOP

In the case of (1) in the representation of path, this system can extract the related facts and calculate the new terms of the relation from these associative values . The inferential path, a_1 IS-A(1.0) a_2 TRANSFER-TO (0.7) a_3 MADE-OF(0.6) a_4, can produce the new relations, a_1 (0.7) a_3, a_1 (0.42) a_4 by equation (3).

$$\begin{aligned} a_1R_{11}a_1 &: R_{11} = R_{11} \\ a_1R_{13}a_3 &: R_{13} = R_{12} \times R_{23} \\ a_1R_{14}a_4 &: R_{14} = R_{12} \times R_{23} \times R_{34} \end{aligned} \tag{3}$$

The mechanism for knowledge Inference-Extraction in this system is composed of Top-down approach and Bottom-up approach. The dashed line (1) means Top-down approach and (2) means Bottom-up approach in Figure 3.

4.1.1. Top-down approach

Top-down approach starts from the input keyword and extracts related facts in a top-down direction. The data extraction mechanism as same as described in chapter 3.1 is applied to the horizontal propagation inside Associative knowledge inference layer in a same manner. Then if wanted, the conditional facts in KLN ,which are connected to the fired node in Associative knowledge inference layer, can be extracted in a top down direction. Top-down algorithm is as following Alg. 2.

Alg. 2 The data extraction algorithm of Top-down approach

Step 1: Input the keyword

Step 2: Search the keyword in the Associative knowledge inference layer.

Step 3: extract the related data by associative extraction algorithm Alg. 1

Step 4: extract the conditional facts of KLN connected to the activated node.

Step 5: Stop

4.1.2. Bottom-up approach

Bottom-up approach is the mechanism of extracting the related facts by propagating conditional input data from the bottom(Input-Reaction layer) to the top(Associative knowledge inference layer). Conditional input data which belong to the different classes may be mixed when they come in to the Input-Reaction layer. If the mixed data come in, the filtering mechanism is performed. In the filtering mechanism, it calculates the firing factor, T_i, which is the criteria for determining the state of firing.

$$T_i = P(C_i|e_1, e_2, \ldots, e_n) = \prod_{k=1}^{n}(C_i|e_k) \tag{4}$$

where C_i is class i and e_i is the evidence i.

If firing factor T_i is over the threshold, q, $(T_i \geq q_i)$, it means that the corresponding class is fired. The KLN of the fired class starts the inferential mechanism and produces the output. The output is propagated to the connected node in the Associative knowledge inference layer and activates that node. After this process, the data extraction mechanism is processed as the same manner of chapter 3.1 to the horizontal direction. The algorithm of Bottom-up approach is as following Alg. 3.

Alg. 3 The data extraction algorithm of Bottom-up approach

Step 1: Input the mixed conditional data belong to the different classes.

Step 2: Calculate the firing factor, T_i according to equation (4).

Step 3: Select the class according to the firing factor.

Step 4: KLN of the selected class starts the inferential mechanism.

Step 5: Extract the related data by Associative extraction algorithm Alg. 1

Step 6: Stop.

5. SIMULATION

We applied this system to the medical diagnostic area for classifying Virus(coxackie virus, echovirus,cold), Rhinitis(Nonallergic ,allergic). We tested with symptom data in the diagnostic area. As a result, we could find that this system can produce the new extracted knowledge using the data extracting mechanism. Figure 4 shows some part of the processing of data extraction by this mechanism.

(Data extraction) The type of input form
1: keyword
2: attribute
3: Quit
select the number ? 1
Top-down approach begins. Enter the keyword? coxakievirus
... Inference path
(A1: coxakievirus A2: echovirus A3 : cold)
... From the hierarchical relation
disease -(INSTANCE-OF) virus
virus -(INSTANCE-OF) coxakievirus
... From the horizontal relation
A1 (SIMILAR-TO 0.9) A2 -(TRANSFORM-TO 0.6) A3
A1 -(AFFECT 0.4) A3
new relations
A1 (0.9) A2
A2 (-0.6) A3
A1(-0.4) A3
Do you want the conditional terms(y/n)? n
(Data extraction) The type of input form
1: keyword
2: attribute
3. Quit
select the number ? 2
Bottom-up approach begins. Input the mixed data ?
......*Truncated* ......
Enter the threshold? 0.7
Selected class is A1 Inferential result :
A1= 0.949500 A2=0.345621 A3=0.000012
... A1 is fired ... Inference path
(A1: coxakievirus A2: echovirus A3 : cold)
... From the hierarchical relation
disease -(INSTANCE-OF) virus
virus -(INSTANCE-OF) coxakievirus
... From the horizontal relation
A1 (SIMILAR-TO 0.9) A2 -(TRANSFORM-TO 0.6) A3
A1 -(AFFECT 0.4) A3
new relations
A1 (0.9) A2
A2 (-0.6) A3
A1(-0.4) A3
Do you want the conditional terms(y/n)? y ... the conditional terms a : age, occurrence rash, characteristic rash , Fever, herpangina, hepatitis, meningitis, pneumonia, pancarditis, respiratory
(Data extraction) The type of input form
1: keyword
2: attribute
3: Quit
select the number ? 3

Figure 4 : The process of Knowledge Inference-Extraction

6. CONCLUSION

Hierarchical modular system with expert knowledge gating mechanism is proposed. This system has the mechanisms of knowledge acquisition, constructing the associative memory and knowledge inference-extraction. We applied this system to the medical diagnostic area for classifying Virus(coxackie virus, echovirus,cold), Rhinitis (Nonallergic ,allergic). As a result of testing, we could find that it can extract the related data considering the expert gating knowledge. easily. This system is expected to be applicable to many areas as data mining, pattern recognition and circumspect decision making method considering associative concepts.

7. REFERENCES

[1] Jeong-Yon Shim, Chong-Sun Hwang Selective Dynamic Fuzzy Neural System *IJCNN'99, Washongton D.C.*

[2] Jeong-Yon Shim, Chong-Sun Hwang Data Extraction from Associative Matrix based on Selective learning system *IJCNN'99, Washongton D.C.*

[3] Allen Natural language understanding

[4] Judea Pearl Probabilistic reasoning in intelligent systems: networks plausible inference em Morgan kaufman Publishers.

[5] Laurene Fausett Fundamentals of Neural Networks *Prentice Hall.*