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S5-63

N93-22211

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A Proposal of Fuzzy Connective with Learning Function and its Application to Fuzzy Retrieval System

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Abstract

A new fuzzy connective and a structure of network constructed by fuzzy connectives are proposed here to overcome a drawback of conventional fuzzy retrieval systems. This network represents a retrieval query and the fuzzy connectives in networks have a learning function to adjust its parameters by data from a database and outputs of a user. The fuzzy retrieval systems employing this network is also constructed. Wherein users can retrieve results even with a query whose attributes do not exist in a database schema and can get satisfactory results for variety of thinkings by learning function.

1. Introduction

Recently, various fuzzy retrieval system[1)2)] had been developed. In fuzzy retrieval systems, users can retrieve data by using queries with fuzzy propositions[3)] such as a query "Search for a hotel of which rate is low AND is near to the business location" in order to "Search for a hotel which is convenient to the business trip". Fuzzy retrieval sytem is a very convenient mechanism for users since they can write the natural language by fuzzy sets in queries, i.e., "Reasonable", "Long" and "Low" and so on. However, it is nearly impossible to obtain results which satisfy us since the meanings of given operators of AND and OR using for obtaining results in queries are quite different for every user, and the number of usable operators[4),5)] are limited within several, i.e., min operator, algebraic product etc.

On the other hand, in the field of decision making problems, a method to optimize the parameters of fuzzy connectives of AND and OR according to the given input and output data was proposed by Dubois and Prade[6)] ,and Maeda et al[7)]. Fuzzy connective proposed by Maeda is based on γ - operator by Zimmermann[8)]. Parameters of the fuzzy connective are optimized for minimizing the square of errors between the observed data and the estimated value of the fuzzy connective. However, the fuzzy connective can not represent the smaller operators more than the algebraic product or the larger operators more than the algeraic sum since this fuzzy connective is constructed by the geometric mean of between the algebraic product and the algebraic sum.

In this paper, first, a new fuzzy connective[9),10)] capable to express whole operators from the drastic product to the drastic sum is formulated and a new learning method to adjust parameters of fuzzy connective is proposed. The proposed fuzzy connective is called fuzzy connective with learning function here. The fuzzy connective with learning function is based on Maeda's operator. The t-norm and t-conorm operators[4),5)] with parameters are linearly combined by using a weighting function, and parameters are adjusted for minimizing the square of error by a steepest descent method.

Second, a new structure of network for representing a query is proposed here. Since the new network represents a query, this network is called the query network here. Query networks put the meaning of the abstractive query into shape by attributes of a database. A query network is constructed by nodes and links which join between nodes. Whole nodes except for in the input layer are constructed by the fuzzy connective with learing function. The retrieval system with query networks can give results which users desire since fuzzy connectives in querry networks have the learning function. The similar fuzzy retrieval system is proposed by Ogawa et al[1)]. However, this method can not derive the importance of attributes in a database since the membership functions are adjusted in the learning stage. The retrieval system that we proposed can not only obtain the importance of attributes in a database also acquire the meanings of AND and OR in users' queries from values of parameters of the fuzzy connective.

First, the fuzzy connective with learning function is formulated. Next, the query network is proposed. Finally, the fuzzy retrieval system with this fuzzy connective and the query network is explained here.

2. Conventional Fuzzy Connective

The operators for representing AND and OR are named generically t-norm and t-conorm, respectively. The t-norm T is a function expressing an operator of $T(x_1,x_2):[0,1] \times [0,1] \to [0,1]$, satisfying the four conditions, i.e., 1)boundary conditions, 2)monotonity, 3)commutativity and 4)associativity. A typical t-norm includes the following operators.

1)Logical product: $x_1 \wedge x_2 = \min\{x_1,x_2\}$ (1)

2)Algebraic product: $x_1 \cdot x_2 = x_1 x_2$ (2)

3)Bounded product: $x_1 \odot x_2 = 0 \vee (x_1+x_2-1)$ (3)

4)Drastic product: $x_1 \curlywedge x_2 = \begin{cases} x_1 & (x_2=1) \\ x_2 & (x_1=1) \\ 0 & (x_1,x_2<1) \end{cases}$ (4)

The t-conorm S is to express an operation of $S(x_1,x_2) = 1-T(1-x_1,1-x_2)$ and also satisfying four conditions in the case of t-norm. In the same way, t-conorm includes the logical sum, algebraic sum, bounded sum and drastic sum, etc.

On the other hand, the following t-norm and t-conorm operators had been proposed by Schweizer[4)], etc.

$$T = 1-((1-x_1)^p+(1-x_2)^p-(1-x_1)^p(1-x_2)^p)^{1/p} \qquad (5)$$

$$S = (x_1{}^p+x_2{}^p-x_1{}^p x_2{}^p)^{1/p}, \qquad p>0 \qquad (6)$$

where, p is a parameter.

By value of parameter p, t-norm of Eq.5 can express logical product, algebraic product, bounded product, drastic product and so on. In the same way, t-conorm can express various operators.

The averaging operators[4] includes arithmetic mean (AM), geometrical mean (GM), conjugated geometrical means (CGM) and so on.

The order of the magnitudes of these operators are expressed by a following relationship.

$$\dot{\wedge} \leqq \odot \leqq \cdot \leqq \wedge \leqq GM \leqq AM \leqq CGM \leqq \vee \leqq \dotplus \leqq \oplus \leqq \dot{\vee} \tag{7}$$

Whole operators which inclues t-norm, t-conorm, and averaging operators are called fuzzy connectives here.

3. Fuzzy Connective with Learning Function

In various fuzzy retrieval systems, fuzzy connectives play the important role in queries since the different results of the retrieval system are obtained by kinds of fuzzy connectives. Let us consider a query Q with fuzzy propositions $q_1, q_2, \cdots, q_t$. For instant, a query Q is expresed as follows:

$$Q = (q_1 \cap q_2) \cup (q_3 \cup q_4) \cap \cdots \cap (q_{t-1} \cup q_t) \tag{8}$$

where, $\cap$ is intersection and $\cup$ is union.

Given the data $x_1, x_2, \cdots, x_t$ for $q_1, q_2, \cdots, q_t$ respectively, the following membership value μ_Q is considered.

- In the case of logical product and logical sum,

$$\mu_Q = (\mu q_1 \wedge \mu q_2) \vee (\mu q_3 \vee \mu q_4) \wedge \cdots \wedge (\mu q_{t-1} \vee \mu q_t). \tag{9}$$

- In the case of algebraic product and algebraic sum,

$$\mu_Q = (\mu q_1 \cdot \mu q_2) \dotplus (\mu q_3 \dotplus \mu q_4) \cdot \cdots \cdot (\mu q_{t-1} \dotplus \mu q_t). \tag{10}$$

In general,

$$\mu_Q = (\mu q_1 \textcircled{T} \mu q_2) \textcircled{\perp} (\mu q_3 \textcircled{\perp} \mu q_4) \textcircled{T} \cdots \textcircled{T} (\mu q_{t-1} \textcircled{\perp} \mu q_t). \tag{11}$$

where, $\textcircled{T}$ shows t-norm and $\textcircled{\perp}$ shows t-conorm.

When we use the conventional retrieval systems, we can not determine the optimum operator to obtain the results we desire since there are so many kinds of fuzzy connectives. Moreover, since there is no operator which is capable of representing from drastic product $\dot{\wedge}$ through drastic sum $\dot{\vee}$ in Eq.7, and has the learning function for adjusting parameters of itself to the meanings of AND and OR for every user, it is difficult to employ the fuzzy connective as AND or OR operator.

In ordert to solve this problem, we propose a following new fuzzy connective which can represent a whole operator in Eq.7.

$$\hat{y} = m\ S + (1-m)\ T \tag{12}$$

where,

$$m = p_1-(p_1-p_2)x_1-(p_1-p_3)x_2$$
$$p_1 \leqq p_2,p_3, \quad 0 \leqq p_1,p_2,p_3 \leqq 1, \quad 0 \leqq -p_1+p_2+p_3 \leqq 1 \qquad (13)$$

and p_1, p_2, p_3 are parameters.

T and S in Eq.12 represents t-norm and t-conorm proposed by Schweizer, Yager, and Dombi etc, respectively. For instance, when t-norm and t-conorm proposed by Schweizer are used, T and S are expressed by the following equations using parameters p_4 and p_5.

$$T = 1-((1-x_1)^{p_4}+(1-x_2)^{p_4}-(1-x_1)^{p_4}(1-x_2)^{p_4})^{1/p_4} \qquad (14)$$
$$S = (x_1^{p_5}+x_2^{p_5}-x_1^{p_5}x_2^{p_5})^{1/p_5}, \qquad p_4,\ p_5>0 \qquad (15)$$

In the fuzzy connective of Eq.12, t-norm T and t-conorm S are linearly combined by using a value of m which can be derived from the values of x_1 and x_2 by Eq.13. Therefore, the weighted operator between t-norm and t-conorm is derived according to values of x_1 and x_2.

An example of the relationship between input and output of the proposed fuzzy connective is shown in Fig.1 wherein the operator is set to emphasize t-norm when the values of x_1 and x_2 are small while the operator emphasizes t-conorm when the values of x_1 and x_2 are large, and it emphasizes t-conorm further for a larger input value of x_1.

Now, let's explain the learning function of the proposed fuzzy connective. When an output y to the input x_1 and x_2 are given, the proposed fuzzy connective is capable to adjust its parameters by a steepest descent method for minimizing the square E of error between the output y and the output $\hat{y}$ of the fuzzy connective.

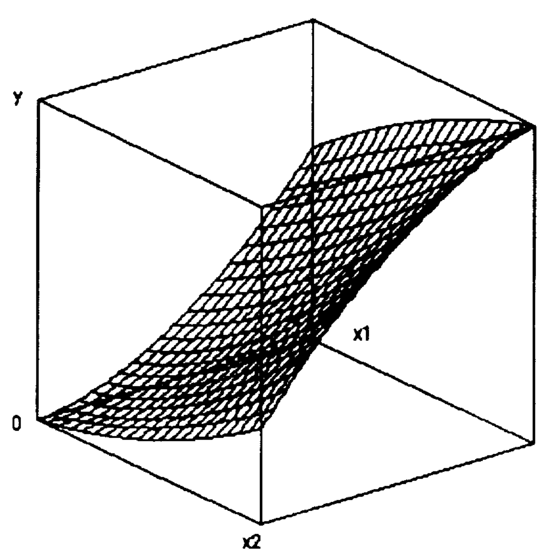


Fig.1 An Example of Relationship Between Input and Output of Fuzzy Connective with Learning Function

$$E = (\hat{y}-y)^2/2 \tag{16}$$

By using a steepest descent, the amounts of corrections of parameters p_j, $j=1,2,\cdots,5$ in Eq.12 to 15 are revised by the following equation.

$$\begin{aligned} p_j^{t+1} &= p_j^t + \Delta p_j \\ &= p_j^t - \alpha \left(\partial E / \partial p_j \right) \end{aligned} \tag{17}$$

where, p_j^t is the t-th revised parameter p_j, and α is a learning coefficient.

$\partial E/ \partial p_j$ which is an effect of minute change of parameter p_j to the error E, can be expressed by the following equation.

$$\frac{\partial E}{\partial p_j} = \frac{\partial E}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial p_j} = (\hat{y}-y) \times \frac{\partial \hat{y}}{\partial p_j} \tag{18}$$

$\partial \hat{y}/ \partial p_j$ can be derived from Eqs.12 to 15 by the following equation.

$$\frac{\partial \hat{y}}{\partial p_1} = (1-x_1-x_2) \times (S-T) \tag{19}$$

$$\frac{\partial \hat{y}}{\partial p_2} = x_1 \times (S-T) \tag{20}$$

$$\frac{\partial \hat{y}}{\partial p_3} = x_2 \times (S-T) \tag{21}$$

$$\frac{\partial \hat{y}}{\partial p_4} = (1-m) \times \frac{\partial T}{\partial p_4} \tag{22}$$

$$\frac{\partial \hat{y}}{\partial p_5} = m \times \frac{\partial S}{\partial p_5} \tag{23}$$

When t-norm T and t-conorm S are defined by Schweizer's ones, Eq.22 and Eq.23 are revised as the following equations.

$$\begin{aligned} \frac{\partial \hat{y}}{\partial p_4} = (1-m)(1-T)\Big(&\frac{1}{p_4^2} \log((1-x_1)^{p_4}+(1-x_2)^{p_4}-(1-x_1)^{p_4}(1-x_2)^{p_4}) \\ &- \frac{1}{p_4((1-x_1)^{p_4}+(1-x_2)^{p_4}-(1-x_1)^{p_4}(1-x_2)^{p_4})} ((1-x_1)^{p_4}\log(1-x_1) \\ &+(1-x_2)^{p_4}\log(1-x_2)-(1-x_1)^{p_4}(1-x_2)^{p_4}\log(1-x_1)(1-x_2))\Big) \end{aligned} \tag{24}$$

$$\begin{aligned} \frac{\partial \hat{y}}{\partial p_5} = mS\Big(&- \frac{1}{p_5^2} \log(x_1^{p_5}+x_2^{p_5}-x_1^{p_5}x_2^{p_5}) \\ &+ \frac{1}{p_5(x_1^{p_5}+x_2^{p_5}-x_1^{p_5}x_2^{p_5})} (x_1^{p_5}\log(x_1)+x_2^{p_5}\log(x_2) \\ &-x_1^{p_5}x_2^{p_5}\log(x_1x_2))\Big) \end{aligned} \tag{25}$$

Employing a steepest descent method, the value of E is minimized by repeating Eq.17. Since the proposed fuzzy connective is capable of learning parameters, this fuzzy connective is called the fuzzy connective with learning function here.

Next, let's consider the conditions for constituting AND and OR operators of queries. The commutativity and associativity within four conditions for t-norm and t-conorm are not always satisfied since there are so many kinds of operators constructing AND and OR. Moreover, it is not need that the boundary conditions are satisfied in this case since there are cases that the averaging operators are considered in the queries. However, since no reliability of results would be gained unless a monotonity between the given input data and retrieved output can be established, the satisfaction of monotonity is a must in this case.

Since there are many kinds of fuzzy connectives with learning function in the query network, for instance, the query Q is represented as follows:

$$Q = (q_1 \otimes_1 q_2) \otimes_2 (q_3 \otimes_3 q_4) \otimes_4 \cdots \otimes_{t-2} (q_{t-1} \otimes_{t-1} q_t) \tag{26}$$

where, $\otimes_k$, $k=1,2,\cdots,t-1$ shows the k-th of fuzzy connectives with learning function in the query network.

Since there are cases that we treat fuzzy connectives with n inputs in the queries, let us extend the fuzzy connective with learning function to one which is capable of representing n inputs $x_1, x_2, \cdots, x_n$ as follows.

$$\hat{y} = m \cdot S + (1-m) \cdot T \tag{27}$$

where,

$$m = p_1 - \sum_{j=1}^{n} (p_1 - p_{j+1}) x_j, \quad 0 \leqq p_1, p_2, \cdots, p_{n+1} \leqq 1, \quad 0 \leqq -(n-1)p_1 + \sum_{j=1}^{n} p_j \leqq 1 \tag{28}$$

When t-norm T and t-conorm S are defined by Schweizer's ones,

$$T = 1-(1-\prod_{j=1}^{n}(1-(1-x_j)^{p_{n+2}}))^{1/p_{n+2}} \tag{29}$$

$$S = (1-\prod_{j=1}^{n}(1-x_j^{p_{n+3}}))^{1/p_{n+3}}, \quad p_{n+2},\ p_{n+3} > 0 \tag{30}$$

where $p_1, p_2, \cdots, p_{n+3}$ are parameters.

Next, let's explain the learning method of the fuzzy connective with learning function as same as in the case of two input variables. When the output y to the input $x_1, x_2, \cdots, x_n$ are given, the amounts of corrections of parameters p_j are revised as same as in Eq.17.

$$\begin{aligned} p_j^{t+1} &= p_j^t + \Delta p_j \\ &= p_j^t - \alpha\, (\partial E / \partial p_j), \qquad j=1,2,\cdots,n+3 \end{aligned} \tag{31}$$

$\partial E / \partial p_j$ which is an effect of minute change of parameter p_j to the error E, can be expressed by the following equation.

$$\frac{\partial E}{\partial p_j} = \frac{\partial E}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial p_j} = (\hat{y}-y) \times \frac{\partial \hat{y}}{\partial p_j} \tag{32}$$

$$\frac{\partial \hat{y}}{\partial p_1} = (1-\sum_{i=1}^{n} x_i) \times (S-T) \tag{33}$$

$$\frac{\partial \hat{y}}{\partial p_j} = x_{j-1} \times (S-T) \tag{34}$$

$$\frac{\partial \hat{y}}{\partial p_{n+2}} = (1-m) \times \frac{\partial T}{\partial p_{n+2}} \tag{35}$$

$$\frac{\partial \hat{y}}{\partial p_{n+3}} = m \times \frac{\partial S}{\partial p_{n+3}} \tag{36}$$

Employing a steepest descent method, the value of E is minimized by repeating Eq.31.

A new structure of network for representing a query is proposed here. Since the new network represents a query, this network is called the query network here.

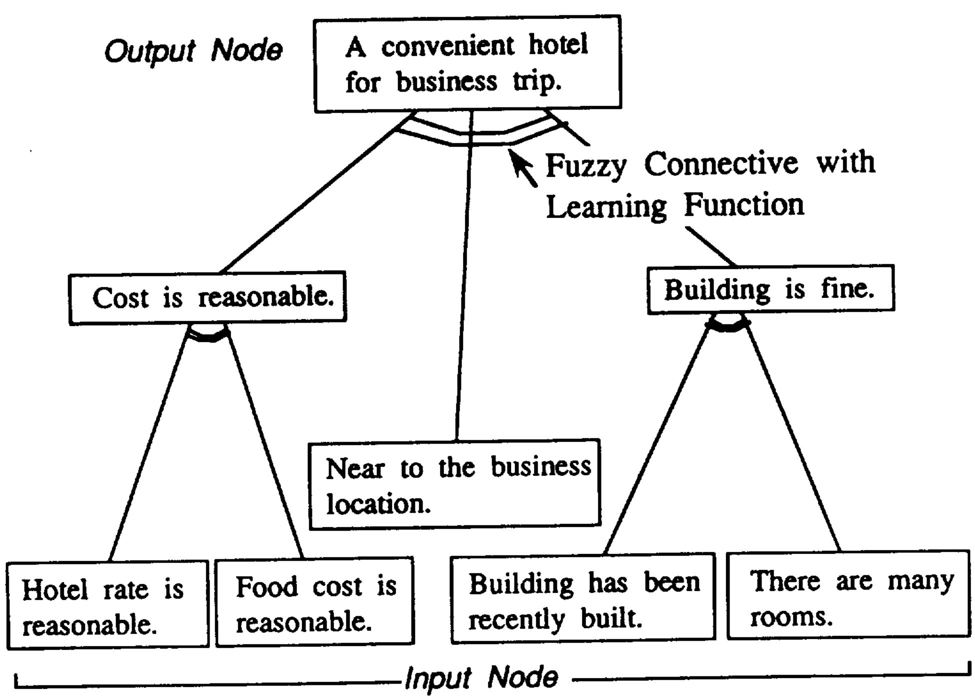


Fig.2 A Example of the Query Network

Let us define the query network as follows :

1) A query network is constructed by nodes N_m, m=1,2, ⋯,M which are joints of network and links L_l, l=1,2, ⋯,M-1 which join a node to other nodes. Nodes in each layer except for in the input and output layer have to join itself to a node in the upper layers and some nodes in the lower layers.
2) There are no links which joint between nodes in the same layer.
3) Every node is constructed by the fuzzy connective with learning function.
4) Every node means a fuzzy proposition.

where, the node in the most upper which is the output layer is called an output-node and nodes in the most lower layer which is the input layer are called input-nodes.

4. Proposed Query Networks

A example of a query network is shown in Fig.2. Now, let us assume that n a five kinds of attributes for searching hotels, i.e., hotel rate, food cost, access time, yaers and rooms are stored in a database. This query network puts the meaning of the output-node which is "Search for a hotel for business trip" into shape by five kinds of attributes through three kinds of nodes which are "Cost is reasonable", "Near to the business location" and "Building is fine" in the middle layer. By using the query network, it is easy to find some hotel by the meanings which is "Search for a hotel for business trip".

Next, let us explain how to learn parameters of fuzzy connective with learning function in query networks when the input x and output y are given. Now, let us represent the output of the i-th fuzzy connective with learning function ordered from output-node as y_i with parameters p_{ij}, j=1,2, ⋯,u. The learning algorithm is based on a backpropagation method for minimizing the square E of error between the output y and the output y_1 of output-node in the query network.

$$E = (y_1 - y)^2/2 \tag{37}$$

In order to obtain the optimum parameters of the i-th fuzzy connective with learning function for minimizing E, an effect of minute change of parameter to the error E is calculated by the following equation.

$$\frac{\partial E}{\partial p^i_j} = \frac{\partial E}{\partial y_1} \times \frac{\partial y_1}{\partial p^i_j}, \quad i=1,2,\cdots,W \tag{38}$$

$\partial E/\partial y_1$ can be derived from Eq.37 by the following equation.

$$\frac{\partial E}{\partial y_1} = y_1 - y \tag{39}$$

$\partial y_1/\partial p^i_j$ can be obtained as follows.

$$\frac{\partial y_1}{\partial p^i_j} = \delta_i \times \frac{\partial y_i}{\partial p^i_j} \tag{40}$$

where, δ_i is

$$\delta_i = \delta_{i-1} \times \frac{\partial y_{i-1}}{\partial p^{i-1}_K}, \qquad i \geqq 2 \tag{41}$$

y_{i-1} is the output of the (i-1) th fuzzy connective with learning function whose input is equal to the output of i-th fuzzy connective with learning function.

We can calculate Eq.40 in the case that the i-th fuzzy connective with learning function is not the output-node. The learning method in the output-node has been explained in the third chapter.

Since δ_i is obtained by repeating Eq.41 in the upper layer more than the i-th fuzzy connective with learning function, $\partial E / \partial p^i_j$ in Eq.38 can be calculated. Therefore, the amounts of corrections of parameters p^i_j in Eq.38 to 41 are revised by the following equation.

$$\begin{aligned} p^i{}_j{}^{t+1} &= p^i{}_j{}^t + \Delta p^i_j \\ &= p^i{}_j{}^t - \beta\,(\partial E / \partial p^i_j) \end{aligned} \tag{42}$$

where, $p^i{}_j{}^t$ is the t-th revised parameter p^i_j, and β is a learning coefficient. The value of E is minimized by repeating Eq.42.

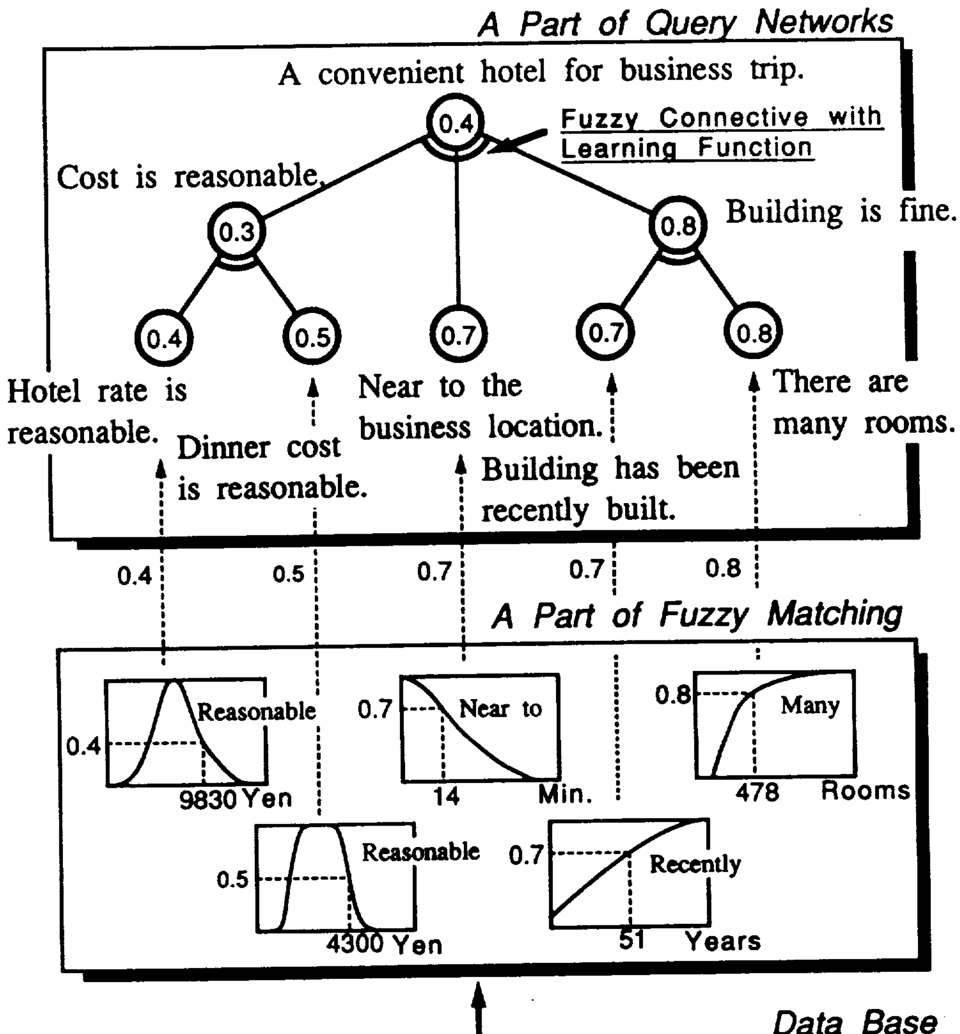
5. Fuzzy Retrieval System

In order to show the usefulness of the fuzzy connective with learning function and the query network, these mechanism are applied to the fuzzy retrieval system.

A conceptual drawing of developed retrieval system is shown in Fig.3. Data in a database are converted into membership values by using membership functions in the fuzzy matching part. These membership values are input to input-nodes of the query network. The results of the retrival system from the output-node after adjusted fuzzy connectives are obtained.

Now, let us consider here a user who search for a convenient hotel for business trip from a database stored 100 hotels near Osaka shown in Table 1. In the proposed fuzzy retrieval system, the following query network shown in Fig.2 is already constructed.

Search for a convenient hotel for business trip.
= Search for a hotel of which cost is reasonable
and(or) is near to the business location
and(or) whose building is fine.
= Search for a hotel of which rate is reasonable
and(or) of which food cost is reasonable
and(or) is near to the business location
and(or) whose building has been recently built
and(or) has so many rooms.



Data Base

No.	Hotel Name	Hotel rate	Dinner Cost	Time	Year	Rooms
2	Osaka Hilton International	17000	3700	14	61	514
1	Osaka Dai-ichi Hotel	9830	4300	18	51	478
:	:	:	:	:	:	:
100	Hotel Sun Garden	5700	1500	58	45	120

Fig.3 Conceptional Drawing of Developed Fuzzy Retrieval System

The steps for retrieving are represented as follows.

1)The system displays 10 hotels as sample data which represent some kinds of sets constructed by five attribute. A user gives estimations of sample data in [0,100] according to the query which is "Search for a convenient hotel for business trip" to the system.

2)Parameters of whole fuzzy connectives with learning function in the query network are adjusted by learning algorithms in the third and forth chapter.

Table 1 A Database of Hotel near Osaka

No.	Hotel Name	Hotel Rate	Dinner Cost	Access Time	Year	Rooms
1	Osaka Hilton International	17000	3700	14	61	514
2	Osaka Dai-ichi Hotel	9830	4300	18	51	478
3	Hotel Hanshin	7800	3000	34	57	209
4	Osaka Terminal Hotel	8500	3800	38	58	664
5	Osaka ANA Hotel Sheraton	12500	5000	54	59	500
6	Dojima Hotel	10000	5000	26	59	134
7	Osaka Grand Hotel	9300	1500	30	33	349
8	Royal Hotel	12500	10000	6	40	1246
9	Hotel NCB	5500	1000	42	50	174
10	Umeda OS Hotel	6500	3000	48	49	283
11	Osaka Tokyu Inn	7800	1800	20	53	402
12	Hotel Kitahachi	5500	1000	56	21	38
13	Maruichi Hotel	4800	1000	12	44	44
14	Hokke Club Osaka	6100	2000	25	41	307
15	Hotel Kansai	4800	1000	37	45	711
16	Hotel Osaka World	5500	1000	48	57	202
17	Osaka ShampiaChampagne Hotel	6100	2000	40	51	300
18	Hotel Kurebe Umeda	5500	3000	14	60	282
19	East Hotel	5200	2700	20	58	144
20	Toko Hotel	5900	2500	58	54	300
21	Hotel Plaza Osaka	5500	2000	47	56	113
22	Osaka Tokyu Hotel	9000	4500	38	54	340
23	Shin-Hankyu Hotel	7800	3000	31	39	993
24	Kishu Railway Hotel	5500	1500	15	55	66
25	Hotel Sunroute Umeda	6000	1500	42	58	218
26	Mitsui Aurburn Hotel Osaka	6500	3500	55	53	405
27	Toyo Hotel	8800	3500	60	40	528
:	:	:	:	:	:	:
100	Hotel Sun Garden	5700	1500	58	45	120

3)The membership values calculated in the fuzzy matching part are input into the input layer of the query network. After the fuzzy connectives with learning function are fixed in the learning stage, the system can retrieve some hotels which users desire.

Fig.4 shows a input display for the 10 sample hotel data estimated by the user. In Fig.4, the degrees of convenience to the business trip that the user provided for the learning are shown.

Fig.5 shows the results after the learning stage. In order to shows the robustness of this learing algorithm, the result of errors between the checking data which a user estimated except for the learning data and the output of the system is also shown. Since the errors between the user's data and the output are small not only for the learning data but also for the checking data, we can obtain the optimum results by this retrieval system.

Close Learn

Order	Hotel_Name	H. Rate	D. Cost	A. Time	Year	Rooms	Grade
1	A	7500	2500	102	48	280	[40]
2	B	8000	4000	120	55	366	[37]
3	C	9500	6000	80	58	300	[50]
4	D	12000	8000	71	61	600	[15]
5	E	6800	1500	47	49	100	[67]
6	F	8500	5000	76	51	778	[57]
7	G	6300	2580	81	63	167	[90]
8	H	10000	2500	38	33	348	[44]
9	I	12000	4500	103	45	74	[12]
10	J	7000	3000	108	41	207	[34]

Fig.4 Input Display and Degrees of Hotel List Proved User for the Learning

Fig.6 shows the results of weights of links in the query network. Since both links between the output-node and the middle node which represents "cost is reasonable" and links between this middle node and the input-node which represents "hotel rate is reasonable" are written by bold lines, it means that the user considers the hotel rate is more important than the access convenience of hotel and so on. Fig.7 shows the results of hotels near Osaka. Fig.8 shows a photograph of the eighth hotel. Fig.9 shows the other results of hotel near Yokohama which are retrieved from the different database by the adjusted fuzzy connective with learning function. From these results shown in Fig.7 and Fig.9, users can determine the hotel that they want to stay at.

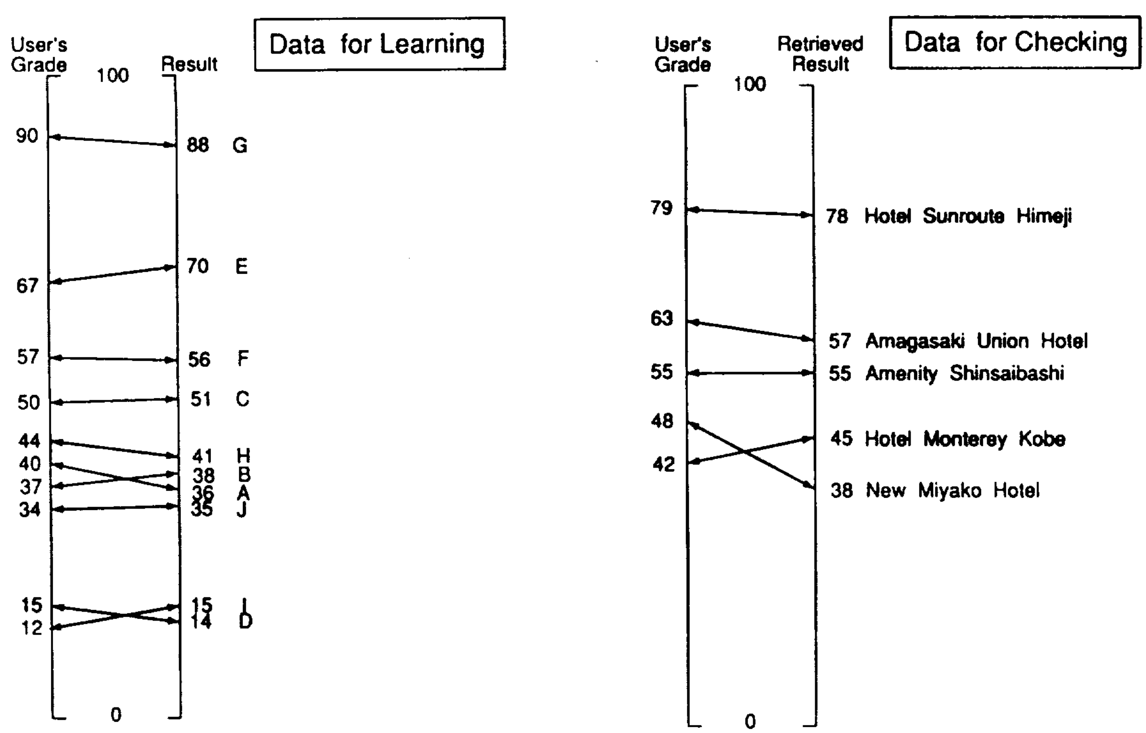


Fig.5 Results of Training Data and Checking Data

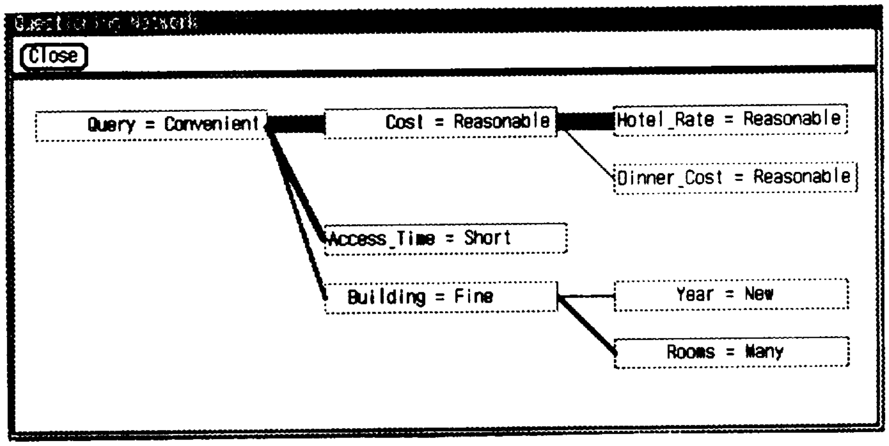
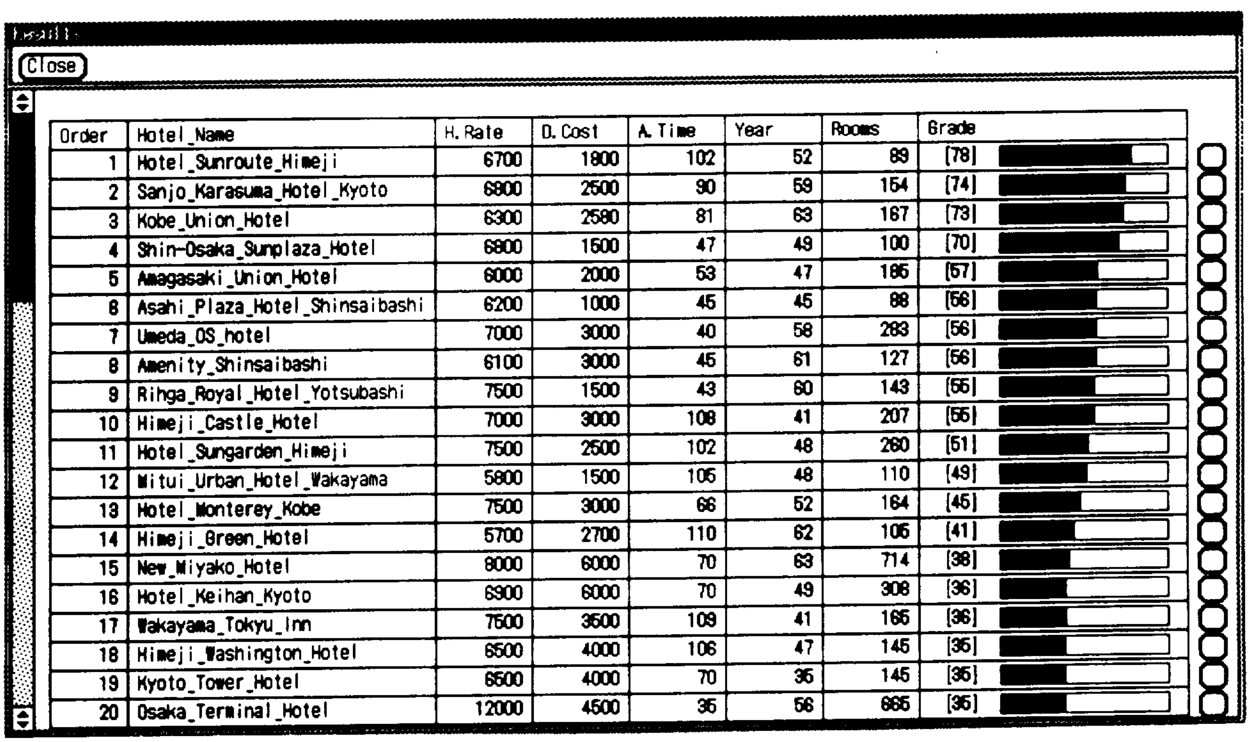


Fig.6 Results of Weights of Links in the Query Network



Order	Hotel_Name	H. Rate	D. Cost	A. Time	Year	Rooms	Grade
1	Hotel_Sunroute_Himeji	6700	1800	102	52	89	[78]
2	Sanjo_Karasuma_Hotel_Kyoto	6800	2500	90	59	154	[74]
3	Kobe_Union_Hotel	6300	2580	81	63	167	[73]
4	Shin-Osaka_Sunplaza_Hotel	6800	1500	47	49	100	[70]
5	Amagasaki_Union_Hotel	6000	2000	53	47	185	[57]
6	Asahi_Plaza_Hotel_Shinsaibashi	6200	1000	45	45	88	[56]
7	Umeda_OS_hotel	7000	3000	40	58	283	[56]
8	Amenity_Shinsaibashi	6100	3000	45	61	127	[56]
9	Rihga_Royal_Hotel_Yotsubashi	7500	1500	43	60	143	[55]
10	Himeji_Castle_Hotel	7000	3000	108	41	207	[55]
11	Hotel_Sungarden_Himeji	7500	2500	102	48	260	[51]
12	Mitui_Urban_Hotel_Wakayama	5800	1500	105	48	110	[49]
13	Hotel_Monterey_Kobe	7500	3000	66	52	164	[45]
14	Himeji_Green_Hotel	5700	2700	110	62	106	[41]
15	New_Miyako_Hotel	8000	6000	70	63	714	[38]
16	Hotel_Keihan_Kyoto	6900	6000	70	49	308	[36]
17	Wakayama_Tokyu_Inn	7500	3500	109	41	165	[36]
18	Himeji_Washington_Hotel	6500	4000	106	47	145	[35]
19	Kyoto_Tower_Hotel	6500	4000	70	36	145	[35]
20	Osaka_Terminal_Hotel	12000	4500	36	56	665	[35]

Fig.7 Results of Hotel Near Osaka

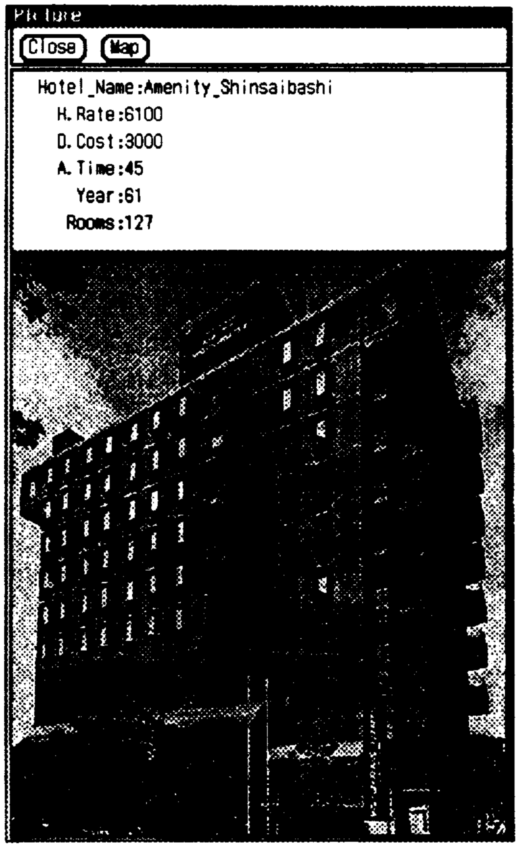


Fig.8 A Potograph of the Eighth Hotel in Results

Close

Order	Hotel_Name	H.Rate	D.Cost	A.Time	Year	Rooms	Grade
1	Pendulum_Inn_Yokohama	6500	1800	18	52	89	[68]
2	Yokohama_Plala_Hotel	6600	3000	37	50	36	[64]
3	Tsurumu_Park_hotel	5800	2200	25	57	315	[53]
4	Heiiwa_Plaza_Hotel	8000	3000	15	61	127	[48]
5	Yokohama_San-Kai_Hotel	6000	5000	15	52	98	[46]
6	Meihin_Hotel	6300	5000	39	61	574	[44]
7	Iisezakicho_Washington_Hotel	9350	6000	19	60	70	[42]
8	Hotel_Umpire	9100	4000	3	55	366	[41]
9	Hotel_Dream_Round	6500	4000	44	53	140	[40]
10	Hotel_Ritchie_Yokohama	9900	1500	16	63	70	[39]
11	Shin-Yokohama_Kokunai_Hotel	8000	4000	37	44	33	[36]
12	Tokyo_Stationery_Hotel	8200	5000	57	52	489	[36]
13	Tanaka-Ya	9000	2500	35	48	260	[36]
14	Suimai	7000	4000	50	51	120	[35]
15	Taimaru_Hotel	4000	4000	25	56	54	[35]
16	Hotel_New_Ground	10600	4000	28	63	145	[35]
17	Ground_Inter-Continental_Hotel	18500	5000	6	62	115	[34]
18	Kakanawa_Tobu_Hotel	9400	2200	43	62	208	[33]
19	Yokohama_Kokusai_Hotel	8700	3000	48	58	100	[32]
20	Weekday_Inn_Tokyo	14700	3500	58	47	653	[21]

Fig.9 Results of Hotel Near Yokohama

5. Conclusion

A fuzzy connective with learning function used a steepest descent method and a query network used a backpropagation method are proposed here. Moreover, a fuzzy retrieval system used by these mechanism is described. In near future, its practical effectiveness has to be proved through more practical applications of this system.

This research is partly performed through Special Coordination Funds of the Science and Technology Agency of the Japanese government.

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