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 systems\(^1\)\(^2\)\(^3\) 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 system 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\(^6\)\(^7\), and Maeda et al\(^8\). Fuzzy connective proposed by Maeda is based on\(^9\)\(^10\) \(\gamma\) operator by Zimmermann\(^11\). 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 algebraic 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
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 \(^*\) 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 learning function. The retrieval system with query networks can give results which users desire since fuzzy connectives in query networks have the learning function. The similar fuzzy retrieval system is proposed by Ogawa et al. However, this method cannot 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 \(T(x_1, x_2): [0,1] \times [0,1] \rightarrow [0,1]\), satisfying the four conditions, i.e., 1) boundary conditions, 2) monotonicity, 3) commutativity and 4) associativity. A typical t-norm includes the following operators.

1) Logical product: \(x_1 \land x_2 = \min\{x_1, x_2\}\) \hspace{1cm} (1)
2) Algebraic product: \(x_1 \cdot x_2 = x_1 x_2\) \hspace{1cm} (2)
3) Bounded product: \(x_1 \cdot^* x_2 = 0 \land (x_1 + x_2 - 1)\) \hspace{1cm} (3)
4) Drastic product: \(x_1 \land^* x_2 = \begin{cases} x_1 & (x_2 = 1) \\ x_2 & (x_1 = 1) \\ 0 & (x_1, x_2 < 1) \end{cases}\) \hspace{1cm} (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, etc.

\[
T = 1 - ((1 - x_1)^p + (1 - x_2)^p - (1 - x_1)(1 - x_2))^\frac{1}{p} \hspace{1cm} (5)
\]
\[
S = (x_1^p + x_2^p - x_1^p x_2^p)^\frac{1}{p} \hspace{1cm} \text{for } p > 0 \hspace{1cm} (6)
\]
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 include 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.

$$\scriptstyle A \leq GM \leq AM \leq CGM \leq V \leq \mathfrak{G} \leq \mathfrak{V}$$

Whole operators which includes 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 $q_1, q_2, \ldots, q_t$. For instance, a query $Q$ is expressed as follows:

$$Q = (q_1 \mathfrak{G} q_2) \mathfrak{G} (q_3 \mathfrak{G} q_4) \mathfrak{G} \cdots \mathfrak{G} (q_{t-1} \mathfrak{G} q_t)$$

where, $\mathfrak{G}$ is intersection and $\mathfrak{V}$ is union.

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

- In the case of logical product and logical sum,
  $$\mu_a = (\mu q_1 \land \mu q_2) \lor (\mu q_3 \lor \mu q_4) \land \cdots \land (\mu q_{t-1} \lor \mu q_t).$$

- In the case of algebraic product and algebraic sum,
  $$\mu_a = (\mu q_1 \cdot \mu q_2) \cdot (\mu q_3 \cdot \mu q_4) \cdot \cdots \cdot (\mu q_{t-1} \cdot \mu q_t).$$

In general,

$$\mu_a = (\mu q_1 \mathfrak{G} \mu q_2) (\mu q_3 \mathfrak{G} \mu q_4) \mathfrak{G} \cdots \mathfrak{G} (\mu q_{t-1} \mathfrak{G} \mu q_t).$$

where, $\mathfrak{G}$ shows t-norm and $\mathfrak{V}$ shows t-conorm.

When we use the conventional retrieval systems, we cannot 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 $\mathfrak{G}$ through drastic sum $\mathfrak{V}$ 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 order to solve this problem, we propose a following new fuzzy connective which can represent a whole operator in Eq.7.

$$\hat{x} = m \cdot S + (1-m) \cdot T$$
where,
\[
m = p_1 - (p_1 - p_2)x_1 - (p_1 - p_3)x_2
\]
\[
p_1 \leq p_2, p_3, \quad 0 \leq p_1, p_2, p_3 \leq 1, \quad 0 \leq -p_1 + p_2 + p_3 \leq 1
\]  \hspace{1cm} (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 \(p_5\).

\[
T = 1 - ((1-x_1)^{p_5} + (1-x_2)^{p_5} - (1-x_1)^{p_5}(1-x_2)^{p_5})^{1/p_4}
\]  \hspace{1cm} (14)
\[
S = (x_1 + x_2 - x_1^{p_5}x_2^{p_5})^{1/p_5}, \quad p_4, p_5 > 0
\]  \hspace{1cm} (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
\[ E = \frac{(\hat{y} - y)^2}{2} \] (16)

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

\[ p_j^{t+1} = p_j^t + \Delta p_j \]
\[ = p_j^t - \alpha \left( \frac{\partial E}{\partial p_j} \right) \] (17)

where, \( p_j^t \) is the \( t \)-th revised parameter \( p_j \), and \( \alpha \) is a learning coefficient.

\[ \frac{\partial E}{\partial p_j} \] which is an effect of minute change of parameter \( p_j \) to the error \( E \), can be expressed by the following equation.

\[ \frac{\partial E}{\partial p_j} = \left( \frac{\partial E}{\partial \hat{y}} \right) \times \left( \frac{\partial \hat{y}}{\partial p_j} \right) \] (18)

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

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

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

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

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

\[ \frac{\partial \hat{y}}{\partial p_5} = m \times \frac{\partial S}{\partial p_5} \] (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.

\[ \frac{\partial \hat{y}}{\partial p_4} = (1-m)(1-T)\left( -\frac{1}{p_4^2} \log((1-x_1)^p_4+(1-x_2)^p_4-(1-x_1)^p_4(1-x_2)^p_4) \right) \]
\[ -\frac{1}{p_4((1-x_1)^p_4+(1-x_2)^p_4-(1-x_1)^p_4(1-x_2)^p_4)} ((1-x_1)^p_4\log(1-x_1) \]
\[ +(1-x_2)^p_4\log(1-x_2)-(1-x_1)^p_4(1-x_2)^p_4\log(1-x_1)(1-x_2)) \] (24)

\[ \frac{\partial \hat{y}}{\partial p_5} = mS\left( -\frac{1}{p_5^2} \log(x_1^p_5+x_2^p_5-x_1^p_5x_2^p_5) \right) \]
\[ +\frac{1}{p_5(x_1^p_5+x_2^p_5-x_1^p_5x_2^p_5)} (x_1^p_5\log(x_1)+x_2^p_5\log(x_2) \]
\[ -x_1^p_5x_2^p_5\log(x_1x_2) \] (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 monotony between the given input data and retrieved output can be established, the satisfaction of monotony 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:

$$Q = (q_1 \odot q_2) \odot_2 (q_3 \otimes q_4) \otimes_4 \cdots \otimes_{t-2}(q_{t-1} \odot_{t-1} q_t)$$

where, $\odot_k$, $k=1,2,\ldots,t-1$ 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 $x_1,x_2,\ldots,x_n$ as follows.

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

where,

$$m = p_i - \sum_{j=1}^{n} (p_i - p_{j+1})x_j,$$

$$0 \leq p_1, p_2, \ldots, p_{n+1} \leq 1, \quad 0 \leq -(n-1)p_1 + \sum_{j=1}^{n} p_j \leq 1$$

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

$$T = 1 - \frac{1}{n} \left(1 - \left(1 - x_j \right)^{p_{n+2}}\right)^{1/p_{n+2}}$$

$$S = \frac{1}{n} \left(1 - \left(1 - x_j \right)^{p_{n+3}}\right)^{1/p_{n+3}}, \quad p_{n+2}, p_{n+3} > 0$$

where $p_1, p_2, \ldots, p_{n+3}$ 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 $x_1, x_2, \ldots, x_n$ are given, the amounts of corrections of parameters $p_j$ are revised as same as in Eq.17.

$$p_j^{t+1} = p_j^t + \Delta p_j$$

$$= p_j^t - \alpha \left( \frac{\beta}{\beta} E/ \frac{\beta}{\beta} p_j \right), \quad j=1,2,\ldots,n+3$$

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

$$\frac{\beta E}{\beta p_j} = \frac{\beta E}{\beta \hat{y}} \times \frac{\beta \hat{y}}{\beta p_j} = (\hat{y} - y) \times \frac{\beta \hat{y}}{\beta p_j}$$

262
\[
\frac{\partial \hat{y}}{\partial p_i} = (1 - \sum_{i=1}^{n} x_i) \times (S-T) \tag{33}
\]

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

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

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

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.

![Diagram of the query network](image-url)

**Fig. 2** A Example of the Query Network
Let us define the query network as follows:

1) A query network is constructed by nodes \( N_m, m=1,2,\ldots,M \) which are joints of network and links \( L_i, i=1,2,\ldots,M-1 \) 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 a five kinds of attributes for searching hotels, i.e., hotel rate, food cost, access time, years 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 \( p_{ij}, j=1,2,\ldots,u \). The learning algorithm is based on a backpropagation method for minimizing the square \( E \) of error between the output \( y \) and the output \( y_i \) of output-node in the query network.

\[
E = \frac{(y_i - y)^2}{2} \tag{37}
\]

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.

\[
\frac{\partial E}{\partial p_{ij}} = \frac{\partial E}{\partial y_i} \times \frac{\partial y_i}{\partial p_{ij}}, \quad i=1,2,\ldots,W \tag{38}
\]

\( \frac{\partial E}{\partial y_i} \) can be derived from Eq.37 by the following equation.

\[
\frac{\partial E}{\partial y_i} = y_i - y \tag{39}
\]

\( \frac{\partial y_i}{\partial p_{ij}} \) can be obtained as follows.

\[
\frac{\partial y_i}{\partial p_{ij}} = \delta_i \times \frac{\partial y_i}{\partial p_{ij}} \tag{40}
\]

where, \( \delta_i \) is
\[ \delta_i = \delta_{i-1} \times \frac{\partial y_{i-1}}{\partial p_{i-1}^t}, \quad i \geq 2 \]  

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

\[
p_j^{i+1} = p_j^i + \Delta p_j^i = p_j^i - \beta \left( \frac{\partial E}{\partial p_j^i} \right) \tag{42}
\]

where, \( p_j^i \) is the \(t\) th revised parameter \( p_j^i \), and \( \beta \) 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 retrieval 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.
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

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

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 learning 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.

267
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 hotels 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

<table>
<thead>
<tr>
<th>Order</th>
<th>Hotel_Name</th>
<th>H. Rate</th>
<th>D. Cost</th>
<th>A. Time</th>
<th>Year</th>
<th>Rooms</th>
<th>Grade</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Hotel_Sunroute_Himeji</td>
<td>6700</td>
<td>1800</td>
<td>102</td>
<td>52</td>
<td>89</td>
<td>[78]</td>
</tr>
<tr>
<td>2</td>
<td>Sanjo_Karasuma_Hotel_Kyoto</td>
<td>6800</td>
<td>2500</td>
<td>90</td>
<td>59</td>
<td>154</td>
<td>[74]</td>
</tr>
<tr>
<td>3</td>
<td>Kobe_Union_Hotel</td>
<td>6300</td>
<td>2500</td>
<td>91</td>
<td>63</td>
<td>187</td>
<td>[79]</td>
</tr>
<tr>
<td>4</td>
<td>Shin-Osaka_Sunplaza_Hotel</td>
<td>6800</td>
<td>1500</td>
<td>47</td>
<td>48</td>
<td>160</td>
<td>[70]</td>
</tr>
<tr>
<td>5</td>
<td>Awagasaki_Union_Hotel</td>
<td>6600</td>
<td>2000</td>
<td>53</td>
<td>47</td>
<td>186</td>
<td>[67]</td>
</tr>
<tr>
<td>6</td>
<td>Asahi_Plaza_Hotel_Shinsaibashi</td>
<td>6200</td>
<td>1000</td>
<td>45</td>
<td>45</td>
<td>88</td>
<td>[68]</td>
</tr>
<tr>
<td>7</td>
<td>Umeda_03_hotel</td>
<td>7000</td>
<td>3000</td>
<td>40</td>
<td>59</td>
<td>238</td>
<td>[66]</td>
</tr>
<tr>
<td>8</td>
<td>Amenity_Shinsaibashi</td>
<td>6100</td>
<td>3000</td>
<td>45</td>
<td>61</td>
<td>127</td>
<td>[66]</td>
</tr>
<tr>
<td>9</td>
<td>Rihga_Royal_Hotel_Yotsubashi</td>
<td>7500</td>
<td>1500</td>
<td>43</td>
<td>60</td>
<td>149</td>
<td>[56]</td>
</tr>
<tr>
<td>10</td>
<td>Himeji.Castle_Hotel</td>
<td>7000</td>
<td>3000</td>
<td>108</td>
<td>41</td>
<td>207</td>
<td>[56]</td>
</tr>
<tr>
<td>11</td>
<td>Hotel_Sungarden_Himeji</td>
<td>7500</td>
<td>2500</td>
<td>102</td>
<td>48</td>
<td>260</td>
<td>[51]</td>
</tr>
<tr>
<td>12</td>
<td>Nitto_Urban_Hotel_Wakayama</td>
<td>5600</td>
<td>1500</td>
<td>105</td>
<td>48</td>
<td>110</td>
<td>[49]</td>
</tr>
<tr>
<td>13</td>
<td>Hotel_Monterey_Kobe</td>
<td>7500</td>
<td>3000</td>
<td>66</td>
<td>52</td>
<td>154</td>
<td>[45]</td>
</tr>
<tr>
<td>14</td>
<td>Himeji_Breen_Hotel</td>
<td>5700</td>
<td>2700</td>
<td>110</td>
<td>62</td>
<td>106</td>
<td>[41]</td>
</tr>
<tr>
<td>15</td>
<td>New_Miyako_Hotel</td>
<td>9000</td>
<td>6000</td>
<td>70</td>
<td>63</td>
<td>714</td>
<td>[38]</td>
</tr>
<tr>
<td>16</td>
<td>Hotel_Keihan_Kyoto</td>
<td>8900</td>
<td>6000</td>
<td>70</td>
<td>63</td>
<td>714</td>
<td>[38]</td>
</tr>
<tr>
<td>17</td>
<td>Wakayama_Tokyu_Tennin</td>
<td>7500</td>
<td>3500</td>
<td>108</td>
<td>41</td>
<td>186</td>
<td>[36]</td>
</tr>
<tr>
<td>18</td>
<td>Himeji_Washington_Hotel</td>
<td>8500</td>
<td>4000</td>
<td>106</td>
<td>47</td>
<td>145</td>
<td>[36]</td>
</tr>
<tr>
<td>19</td>
<td>Kyoto_Tower_Hotel</td>
<td>8500</td>
<td>4000</td>
<td>70</td>
<td>36</td>
<td>145</td>
<td>[36]</td>
</tr>
<tr>
<td>20</td>
<td>Osaka_Terminal_Hotel</td>
<td>12000</td>
<td>4500</td>
<td>36</td>
<td>56</td>
<td>686</td>
<td>[36]</td>
</tr>
</tbody>
</table>

Fig. 7  Results of Hotel Near Osaka

269
Fig. 8 A Photograph of the Eighth Hotel in Results

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.

References
