Development of Neuro-Fuzzy Expert System for Serviceability Assessment of Concrete Bridges

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Abstract

Efforts to develop practical expert systems have been mostly concentrated on how to implement experience-based machine learning successfully. Recently several active researches on machine learning have been undertaken from the viewpoints of knowledge base management. The aim of this study is to develop the Concrete Bridge Rating(Diagnosis) Expert System with machine learning employing the combination of neural networks and bidirectional associative memories (BAM). Introduction of machine learning into this system facilitates knowledge base refinement. By applying the system to an actual in-service bridge, it has been verified that the employed machine learning method using results of questionnaire surveys on bridge experts is effective for the system.

Keywords: concrete bridge, serviceability assessment, expert system, fuzzy rule, neural network, machine learning.

1. INTRODUCTION

The authors have been working for some time on the development of a Concrete Bridge Rating Expert System[1,2] that can evaluate the serviceability of concrete bridges on the basis of knowledge and experience acquired from domain experts. The task of refinement of the knowledge base, however, in the development of a practical expert system has turned out to be very time- and labor-consuming and has been a bottleneck in expert system development.

The final goal of the present system is to evaluate the structural serviceability of bridges on the basis of the specifications of target bridges, environmental conditions, traffic volume, and other subjective information such as one obtained through visual inspection. The inference mechanism in the system first selects a membership function (Π function parameters) defined in the knowledge base on the basis of the knowledge acquired from domain experts to achieve the lowest level subgoals of the diagnostic process. The inference mechanism then combines the subgoals with a higher level subgoals according to Dempster's rule of combination and repeats this process[1]. In evaluating the serviceability which is evaluated by a combination of "load carrying capability" and "durability" of a target bridge, which is the final goal of the expert

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system, the inference mechanism performs fuzzy mapping considering the degree of influence and the degree of confidence, and outputs the result of serviceability evaluation of the bridge accordingly. It has become known, however, that for certain types of inputs, the system sometimes outputs inconsistent results because the relevant knowledge accumulated in the system is incomplete[3]. It is no easy task, however, to refine the knowledge base in the system while maintaining the integrity of the system. Consequently, the procedure of knowledge base management needs to be simplified by introducing machine learning into the expert system.

In this study, an inference system combining the neural network[4] and the bidirectional associative memory (BAM)[5] was constructed as part of the Concrete Bridge Rating Expert System. The results of questionnaire surveys conducted on domain experts during field tests were used as teacher data (objective criteria) to give the system the ability to learn and verify the effectiveness of the learning method.

2. MACHINE LEARNING USING NEURAL NETWORKS

2.1 Concept of Neural Network and Refinement of Knowledge Base of the Expert System

The neural network refers to a method of information processing using a network of processing elements modeled after the structure of the human brain[4]. The reason why the neural network is worthy of note is that it can learn. In other words, the neural network can reorganize itself by altering the strength of connection between the processing units according to some learning algorithm. In the neural network, given an input, the network processes the information, compares the output with the ideal response, and modifies the weights for connections according to the errors. In this way the network reorganizes its own internal structure so that it gives proper outputs corresponding to input data. If applied to the Concrete Bridge Rating Expert System, therefore, the neural network makes it possible to modify the knowledge base easily on the basis of input data on target bridges and the results of serviceability evaluation by experts or of field tests.

The Concrete Bridge Rating Expert System acquires knowledge by defining a membership function for the consequent (part of *IF-THEN* rules that comes after *THEN*) of a fuzzy rule according to the results of questionnaire surveys conducted on domain experts[1,2]. It can be said, therefore, that individual rules reflect the knowledge and experience of those domain experts. Since, however, the inference process involves multidimensional, multistage fuzzy inference, the degree of uncertainty tends to increase as inference progresses, that is, at higher levels of diagnostic process. Since the combination of fuzzy rules varies according to the rules of combination, and rules of combination are usually not compatible with the thinking of the human mind, results that can be obtained by combining rules do not necessarily satisfactory to domain experts. In addition, there is no learning function to improve performance. Nevertheless, fuzzy inference is advantageous in that it is based on *IF-THEN* rules, which permit the representation of knowledge in natural language.

The greatest advantage of inference using the neural network is a powerful learning algorithm. In addition, it can be said that outputs from the neural network-based inference perfectly reflect expert knowledge because the results of serviceability evaluation by domain experts or of field tests are used as teacher data. There are also disadvantages, however, that since inference by the neural network is represented as behavior of the entire network, the inference system becomes a "black box" that makes the representation of knowledge in the form of rules impossible. Also a large network of this type can be less flexible with the addition and alteration of rules. Furthermore, there is a need to deal somehow with ambiguity due to human involvement in constructing a neural network-based bridge rating system.

Thus, at present fuzzy inference and neural network-based inference differ considerably in nature. It is possible, however, to construct a more powerful inference system by overcoming the weaknesses and combining the advantages of the two methods. In order to help prevent the neural network from becoming a black box, in this study subnetworks were constructed for individual subgoals for the floor slab and the main girder in the diagnostic process, and these subnetworks were combined at a higher level. It was also decided that an inference system capable of fuzzy inference would be developed by introducing associative memory.

2.2 Fuzzy Inference System Based on Neural Network

2.2.1 Structure of Inference System

Generally, inferences are drawn according to *IF-THEN* rules. In this study, the *IF-THEN* rules were divided into three parts: *IF-THEN* relationships, antecedents and consequents. In constructing the inference system, the antecedents and consequents were represented by neural networks and were interconnected by bidirectional associative memories (BAM)[5,6]. Fig. 1 shows the structure of the inference system. The *IF-THEN* relationship was represented by two interconnected BAMs (relationship **M**) as shown in Fig. 2. Here, the three levels (input level **I**, middle level **M**, output level **O**) correspond to the antecedent, the concept of the rule, and the consequent, respectively. Each neuron at the input level represents the recall factor[6]

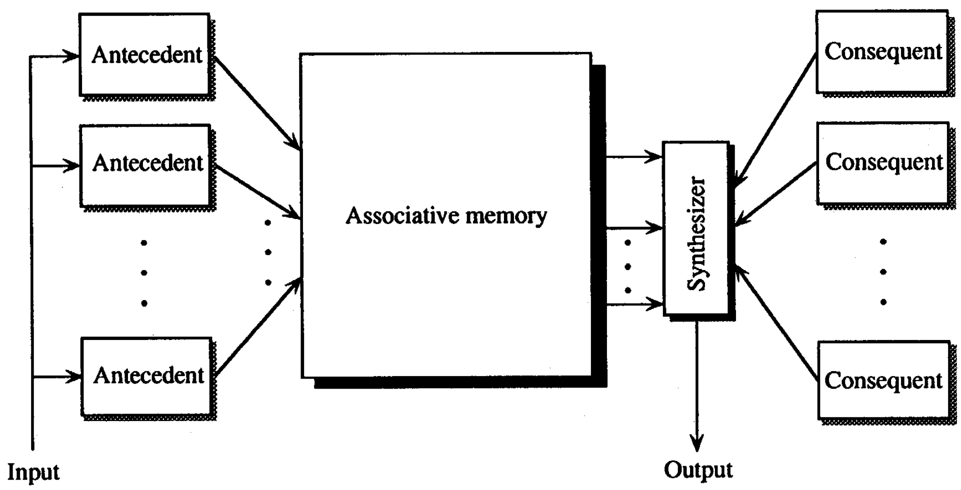

Fig. 1. Structure of Inference System

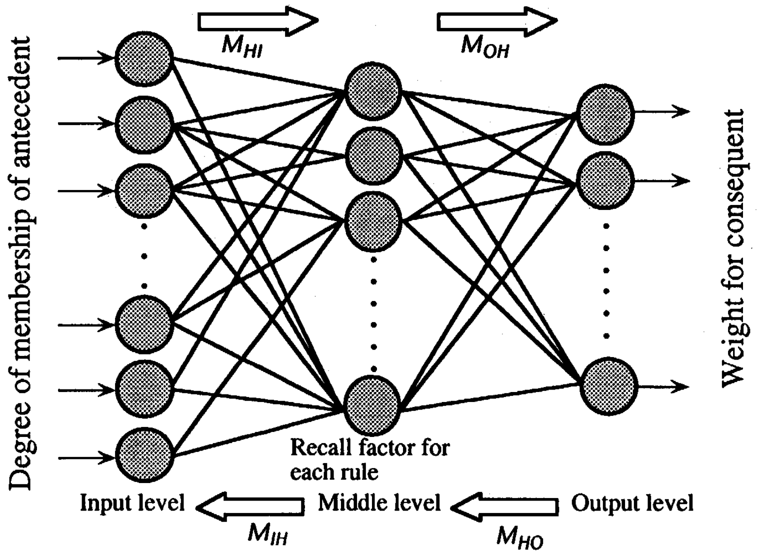

Fig. 2. IF-THEN Relationship Represented by Associative Memory

for the antecedent, and the number of neurons at the input level equals the number of membership functions that define input variables. Each neuron at the middle level represents the recall factor for each rule, and the number of neurons at the middle level equals the number of rules. Similarly, since each neuron at the output level represents the recall factor for the consequent, the number of neurons at the output level equals the number of membership functions that define output variables.

2.2.2 Representation of Fuzzy Rules[7]

A type of fuzzy model that is generally said to be capable of a high degree of representation has been adopted. It is assumed that if input and output are represented by u and y respectively, the object of modeling can be expressed as follows:

$$y = f(u) \tag{1}$$

In this case, the system in question can be expressed using n fuzzy rules:

$$\begin{cases} R_1 : \text{IF } u_1 = C_{11} \text{ and} \cdots \text{and } u_r = C_{1r} \text{ THEN } y_1 = f_1(u) \\ \quad \vdots \qquad\qquad \vdots \qquad\qquad \vdots \qquad\qquad \vdots \\ R_i : \text{IF } u_1 = C_{i1} \text{ and} \cdots \text{and } u_r = C_{ir} \text{ THEN } y_i = f_i(u) \\ \quad \vdots \qquad\qquad \vdots \qquad\qquad \vdots \qquad\qquad \vdots \\ R_n : \text{IF } u_1 = C_{n1} \text{ and} \cdots \text{and } u_r = C_{nr} \text{ THEN } y_n = f_n(u), \end{cases} \tag{2}$$

where, C_{11} to C_{nr} are fuzzy variables.

Usually, $f(u)$ is a linear function, but in this study, a neural network model instead of a linear function is used. The effect of this is similar to that of using a nonlinear equation for the consequent of each inference rule. It is also possible here to identify the overall nonlinear relationship using a single neural network model. For purposes of this study, however, it was decided to use one neural network model for the rule for each subgoal in the diagnostic process constructed for the floor slab and the main girder. This, it is believed, makes a clear representation of the overall nonlinear relationship possible and helps make the model transparent.

The final output **y** can be expressed, using the weight **a** for the consequent determined by associative memory, as follows:

$$\mathbf{y}=\sum_{i=1}^{n} a_i \times y_i / \sum_{i=1}^{n} a_i \tag{3}$$

where, y_i is the output from the i-th neural network, and a_i is the weight for the i-th neural network.

Now let us look at the method of storing rules in associative memories. The associative memory combines neurons at different levels according to the relationships between nodes, that is, depending on whether or not they constitute the same rule. Let us consider rule $i(\mathbf{R}_i)$ in Eq. (2). As Eqs. (2) and (3) indicate, rule $i(\mathbf{R}_i)$ relates to fuzzy variables C_{i1}-C_{ir} and weight a_i for the consequent. Therefore, neurons C_{i1}-C_{ir} at the input level and the neuron for rule $i(\mathbf{R}_i)$ at the middle level are interconnected by "+" links. On the other hand, the neuron for rule $i(\mathbf{R}_i)$ and the other neurons at the input and output levels are interconnected by "-" links assuming that they are reciprocal. Within the input level, neurons corresponding to the same input variable are connected by "-" links, while neurons corresponding to different input variables are considered to be unrelated and are therefore not connected. The weight for each link is determined so that given inputs exactly matching rule i, all the neurons corresponding to rule i fire, but the other neurons do not.

In this study, the strength of connection between the middle level and the output level is defined as the degree of certainty of each rule. By so doing, the certainty factor for each rule can be modified according to the rules of learning based on associative memory. It is to be noted here that the learning here involves the modification of the certainty factor depending on the frequency of reference to the rules.

2.2.3 Inference Process in Associative Memory

The associative memory represents the relationship between the elements from input **u** to state vector **z** at the output level in the form of a discrete time system. Inferences are drawn using the formula given below, and the inference system consists of an input part, a middle part, an output part, and a check point, as shown in Fig. 3.

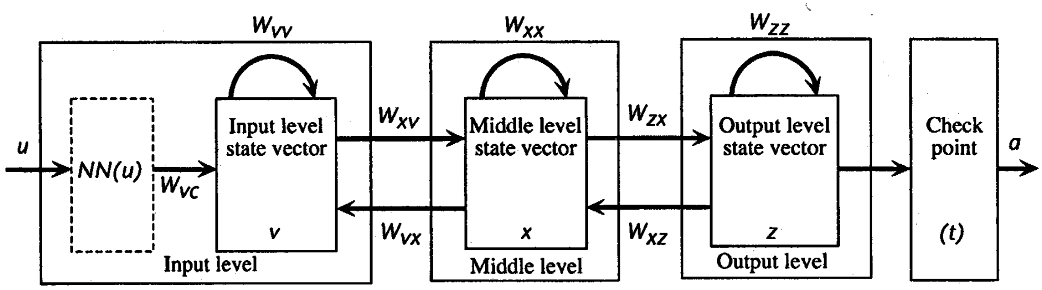

Fig. 3. Inference Process in Associative Memory

$$\begin{cases} c(k) = NN\{u(k)\} \\ v(k+1) = \mathbf{f}\{\boldsymbol{W}_{vc}\ c(k) + \boldsymbol{W}_{vv}\ v(k) + \boldsymbol{W}_{vx}\ x(k)\} \\ x(k+1) = \mathbf{f}\{\boldsymbol{W}_{xv}\ v(k+1) + \boldsymbol{W}_{xx}\ x(k) + \boldsymbol{W}_{xz}\ z(k)\} \\ z(k+1) = \mathbf{f}\{\boldsymbol{W}_{zx}\ x(k+1) + \boldsymbol{W}_{xz}\ z(k)\} \\ v(0) = v_0 \\ x(0) = x_0 \\ z(0) = z_0 \\ \boldsymbol{W}_{vx} = \boldsymbol{W}_{xv}{}^{\mathrm{T}} \\ \boldsymbol{W}_{xz} = \boldsymbol{W}_{zx}{}^{\mathrm{T}} \end{cases} \tag{4}$$

where, $NN(\cdot)$ is a neural network that represents a membership function whose antecedent is a fuzzy variable; $\mathbf{f}(\cdot)$ is a Sigmoid function. $\boldsymbol{W}_{vc}$, $\boldsymbol{W}_{vv}$, $\boldsymbol{W}_{vx}$, $\boldsymbol{W}_{xv}$, $\boldsymbol{W}_{xx}$, $\boldsymbol{W}_{xz}$, $\boldsymbol{W}_{zx}$ and $\boldsymbol{W}_{zz}$ are matrices that represent the weights for the degrees of connection of the links. Especially, the matrices $\boldsymbol{W}_{xz}$ and $\boldsymbol{W}_{zx}$ represent the certainty factors for the rules.

The transition of state until the network reaches the state of equilibrium is a process of choosing the most appropriate rule out of a set of rules. Therefore, inferences corresponding to fuzzy inferences can be drawn by taking out output $\boldsymbol{z}(\mathbf{t})$ at time t before the state of equilibrium is reached and assigning weight $\mathbf{a}$ to the consequent. The higher the certainty factor for a rule, the faster the activation. This means that higher weights can be assigned to consequents with higher certainty factors.

2.3 Method of Fuzzy Rule Modification

This section describes the method of modifying the fuzzy rules. The modification of the rules can be classified either as the modification of the certainty factor or the modification of the neural networks for the consequents. These are described below: *(1) Modification of Certainty of Rules*[7]*:* As mentioned earlier, the certainty factor for a rule is represented by the weight for linkage between the middle level (representing the concept of rules) and the output level (representing the weight for the consequent) in the associative memory. The certainty factor is modified by altering this weight according to the rule of Hebbian learning[8]. Let us consider element W_{ij} in matrix $\boldsymbol{W}_{xz}(\boldsymbol{W}_{zx})$ that represents the certainty factor for a rule. $\boldsymbol{W}_{xz}(\boldsymbol{W}_{zx})$ is modified after a certain number of inferences are drawn, and W_{ij} is modified on an independent time scale using the following formula:

$$\dot{W}_{ij}(t) = -W_{ij}\ (t) + X_i \times R_j \tag{5}$$

where, $W_{ij}(t) \in [0,\infty]$ and $X_i \in \{0,1\}$ represent whether rule i and consequent j are related, and $R_j \in [0,\infty]$ represents the certainty factor consequent j in relation to rule i.

If $X_i = 1$ and R_j=constant and if the value of R_j corresponds to the case where the consequent matches the rule perfectly, the following equation can be derived from Eq. (5):

$$W_{ij}(t) = \exp(-t)\{W_{ij}(0) - R_j\} + R_j \tag{6}$$

Hence, the incremental modification ΔW_{ij} of W_{ij} at the k-th($k \geq 1$) modification can be given by

$$\Delta W_{ij} = \exp[-T(k-1)]\{1 - \exp[-\delta T]\}\{R_j - W_{ij}\} \tag{7}$$

where, $T(k-1)$ is the time (on an independent time scale of neuron j) when the (k-1)-th modification is made, and $T(0) \geq 0$. δT is the time from the (k-1)-th modification to k-th modification. It is assumed that δT is determined by a quantity that is inversely proportional to the current weight W_{ij} and is proportional to the frequency(Σa) at which rule $i(\mathbf{R}_i)$ is referred to:

$$\delta T = \beta \times \min\{1, \eta \times (\Sigma a) / W_{ij}(k)\} \tag{8}$$

where, β and η are positive constants; β is the maximum time elapsed during a single modification process, and η is the influence of the frequency of reference and the certainty factor on the time δT. The modification rules defined by Eqs. (7) and (8) indicate that the amount of modification corresponding to the certainty factor for a rule is determined so that it is proportional to the cumulative weight for the consequent of the rule in relation to the output and is inversely proportional to the current certainty factor. This means that learning about rules that are referred to frequently and are less certain is faster, while learning about rules that are not referred to often and have higher certainty factors is slow. As the learning process progresses, W_{ij} gradually approaches R_j. Learning does not take place, however, when $\delta T = 0$. The certainty factor is automatically modified in the system.

(2)Modification of Neural Network Models for Consequents: Learning by the neural networks for the consequents takes place when data on relevant case studies (in this study, data on the evaluation of bridges) has been acquired or when outputs of the system differ from the ideal responses. Since each subgoal is modeled as a subnetwork, there is no need to modify the knowledge for all neural network models; only the subgoals related to the input data have to be modified. In addition, since the learning method uses a back propagation algorithm[4], all that has to be done is to add pairs of input and output data as new teacher data or to modify existing teacher data accordingly. Thus, the time needed to refine the knowledge base can be reduced.

3. DEVELOPMENT OF NEURO-FUZZY EXPERT SYSTEM

3.1 Acquisition of Initial Knowledge

Acquisition of initial knowledge is of vital importance to the construction of neural networks. An expert system can best be constructed using data obtained from past diagnoses. In the case of the expert system considered here, however, it is impossible to collect enough data on past diagnoses encompassing all the possible input items needed in the diagnostic process. In this study, therefore, the knowledge base of the previous(original) system[1,2] was used as the initial knowledge of the new system. The acquisition procedure is described below using an example of diagnosis of the "level of flexural cracks".

In the present rating(diagnostic) process, the "level of flexural cracks" is diagnosed in terms of "degree of cracking" and "degree of free lime deposition" (see Fig. 4). In evaluating the soundness of bridges with respect to the "level of flexural cracks", it is general practice to use "degree of cracking" rather than "degree of free lime deposition" as a key indicator. On the basis of the input conditions regarding "degree of cracking", a model can be constructed as follows:

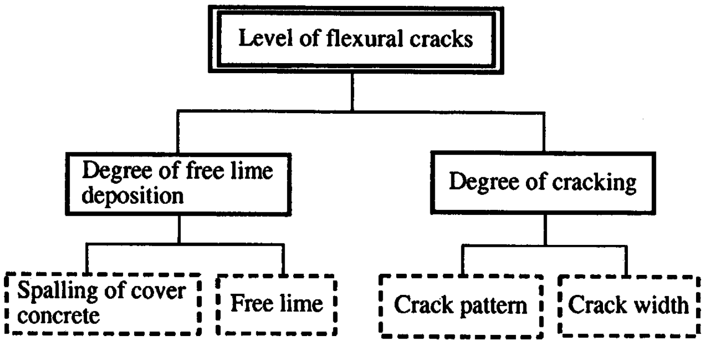

Fig. 4. Diagnostic Process for Level of Flexural Cracks

$$\begin{cases} \textbf{Rule 1}: \text{IF } x_1 = A_1 \text{ and } x_2 = B_1 \text{ THEN } y = f_1(x_1, x_2, x_3, x_4) \\ \textbf{Rule 2}: \text{IF } x_1 = A_1 \text{ and } x_2 = B_2 \text{ THEN } y = f_2(x_1, x_2, x_3, x_4) \\ \textbf{Rule 3}: \text{IF } x_1 = A_1 \text{ and } x_2 = B_3 \text{ THEN } y = f_3(x_1, x_2, x_3, x_4) \\ \quad\vdots \qquad\qquad \vdots \qquad\qquad \vdots \qquad\qquad \vdots \\ \textbf{Rule 7}: \text{IF } x_1 = A_3 \text{ and } x_2 = B_1 \text{ THEN } y = f_7(x_1, x_2, x_3, x_4) \\ \textbf{Rule 8}: \text{IF } x_1 = A_3 \text{ and } x_2 = B_2 \text{ THEN } y = f_8(x_1, x_2, x_3, x_4) \\ \textbf{Rule 9}: \text{IF } x_1 = A_3 \text{ and } x_2 = B_3 \text{ THEN } y = f_9(x_1, x_2, x_3, x_4) \end{cases} \tag{9}$$

where, x_1 : crack condition, x_2 : crack width, x_3 : lost concrete, x_4 : free lime,

A_1 : many cracks, A_2 : some cracks, A_3 : few cracks,

B_1 : large crack width, B_2 : medium crack width, B_3 : small crack width,

y= [dangerous, slightly dangerous, moderate, slightly safe, safe]: result of evaluation of level of flexural cracks,

$f(\cdot)$: neural network model

As shown above, a total of nine(f_1-f_9) consequent neural network models corresponding to the nine rules are constructed. The previous system[1,2] used an inference method under which membership functions defined for individual rules were interconnected according to Dempster's rule of combination. For the present system, therefore, inferences are drawn, according to Dempster's rule of combination, for all of the possible combinations of conditions for each rule, and the results thus obtained are used as teacher data needed for initial knowledge acquisition. Thus, the system uses the teacher data to acquire initial knowledge following a back propagation algorithm. Acquiring the initial knowledge in this manner ensures the reliability of diagnosis at least comparable to that of the previous system.

Turning now to the method of determining the fuzzy variable for the antecedent of an *IF-THEN* rule, a membership function representing the fuzzy variable for the antecedent can be easily expressed using the neural network, that is, by letting the system learn from teacher data that represents membership functions discretely according to the back propagation algorithm. If, for example, a fuzzy set regarding "crack width" shown below is given, the membership function as shown in Fig. 5 can be obtained.

$$\begin{cases} \text{Small crack width :} & \textbf{\textit{Small}} = \{1.0/0.0,\ 0.8/0.2,\ 0.2/0.3,\ 0.0/0.4\} \\ \text{Medium crack width :} & \textbf{\textit{Medium}} = \{0.0/0.1,\ 0.2/0.2,\ 0.8/0.3,\ 1.0/0.4,\ 0.9/0.5, \\ & \qquad 0.5/0.6,\ 0.2/0.7,\ 0.0/0.8\} \\ \text{Large crack width :} & \textbf{\textit{Big}} = \{0.0/0.4,\ 0.2/0.5,\ 0.6/0.6,\ 0.8/0.7,\ 0.95/0.8, \\ & \qquad 1.0/0.9,\ 1.0/1.0\} \end{cases} \tag{10}$$

Finally, let us consider the weighting of connections in the associative memory. As discussed in Section 2.2.2, the associative memory determines the strength of connection between neurons at each level depending on whether they constitute the same rules. Consequently, in the case of the "level of flexural cracks", an associative memory network is constructed on the basis of Eq. (9), as shown in Fig. 6. Of the combination matrices defined according to Fig. 6, $\boldsymbol{W}_{xz}$ that represents the certainty factors for the rules can be expressed as follows:

$$\boldsymbol{W}_{xz} = \left(\mathbf{C}_{xz} \right) \begin{pmatrix} 1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \\ -1 & 1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \\ -1 & -1 & 1 & -1 & -1 & -1 & -1 & -1 & -1 \\ -1 & -1 & -1 & 1 & -1 & -1 & -1 & -1 & -1 \\ -1 & -1 & -1 & -1 & 1 & -1 & -1 & -1 & -1 \\ -1 & -1 & -1 & -1 & -1 & 1 & -1 & -1 & -1 \\ -1 & -1 & -1 & -1 & -1 & -1 & 1 & -1 & -1 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & 1 & -1 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & 1 \end{pmatrix} \tag{11}$$

where, $\mathbf{C}_{xz}$ is a matrix in the combination matrix $\boldsymbol{W}_{xz}$ that represents the certainty for each rule. In this study, the certainty factor for the knowledge acquired from the previous system was assumed to be 60% and that was applied to all rules.

Thus, the initial knowledge was acquired by repeating the above procedure for all subgoals and final goals.

3.2 Setting up Objective Criteria

As mentioned earlier, teacher data is necessary in order to refine the knowledge using

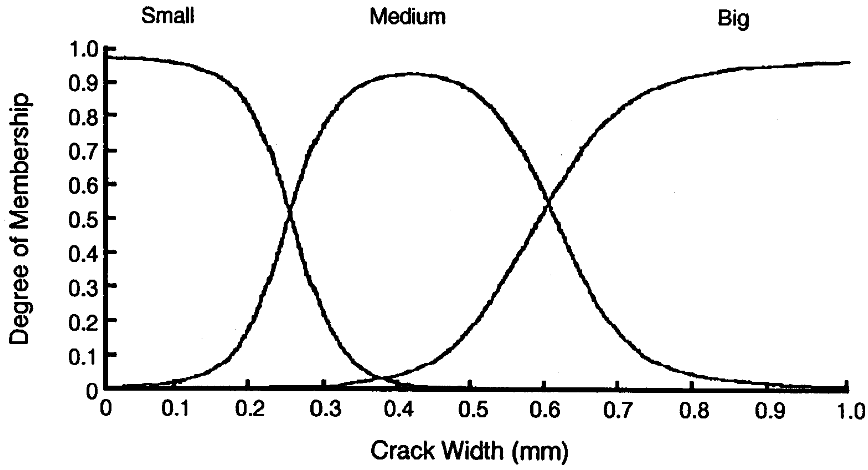

Fig. 5. Membership Function Representing Crack Width

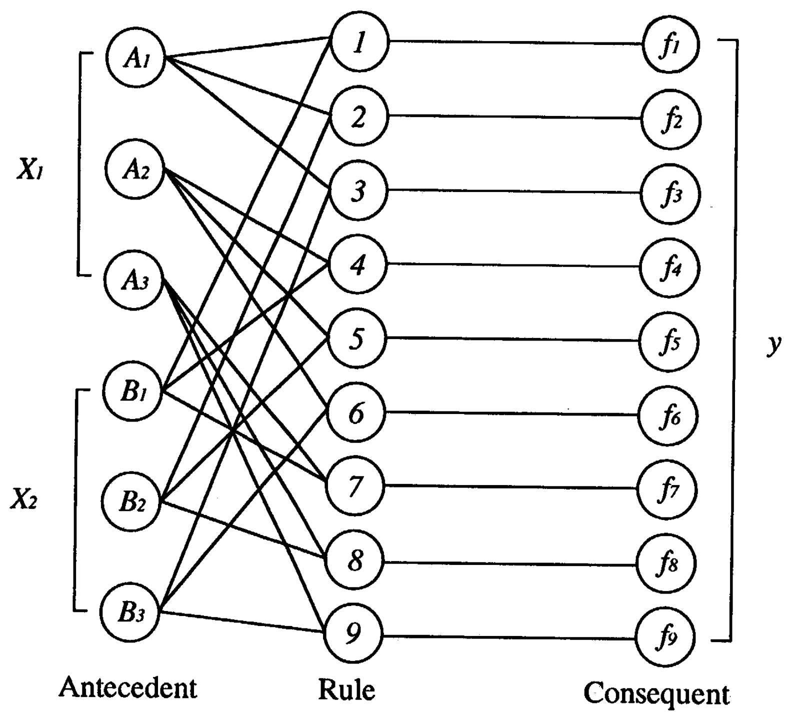

Fig. 6. Associative Memory Network

the neural networks. Hence, results of diagnoses based on field data must be used as teacher data (objective criteria) to refine the knowledge base in the consequent neural networks. Results of evaluation of bridges based on field data are much more objective and reliable than diagnoses made by the present "Concrete Bridge Rating Expert System". It is therefore desirable that such evaluation data be used as teacher data(objective criteria) for knowledge base refinement. Since, however, the system forms integrated judgments on the soundness of bridges(see Section 3.3), outputs of the system cannot be compared directly with individual evaluation items, such as the safety factor, probability of failure, etc. This means that definite judgments on the degrees of modification of the rules cannot be formed. In this study, therefore, it is assumed that the knowledge base can be refined on the basis of field data by relating the system and field testing via domain experts' judgments, and the knowledge base was refined using data obtained mainly from questionnaires[9] on the serviceability evaluation of target bridges filled out by domain experts.

The questionnaire surveys on serviceability evaluation were conducted on more than one expert. The respondents were asked to answer questions regarding the damage state of the bridges after conducting visual inspection and observation. Since the results of evaluation were expected to vary depending on the experience of domain experts, the respondents were chosen carefully so that experts with as much experience as possible were included. In the questionnaire, each respondent was asked to rate the serviceability, load-carrying capacity and durability of the bridges, as well as other items corresponding to the subgoals in the Concrete Bridge Rating Expert System, on a scale of 100. The respondents were also asked to form subjective judgments on the need for repair and rehabilitation, and the remaining service life of the bridges.

The scores thus obtained were categorized into five groups, namely, 0-19, 20-39, 40-59, 60-79, 80-100, and these groups were modified with the terms "dangerous," "slightly dangerous," "moderate," "slightly safe" and "safe" respectively. By comparing these scores directly with the results of rating by the system, the knowledge base can be refined relatively easily and reliably.

3.3 System Configuration

Fig. 7 shows the configuration of the expert system. The knowledge base, the inference

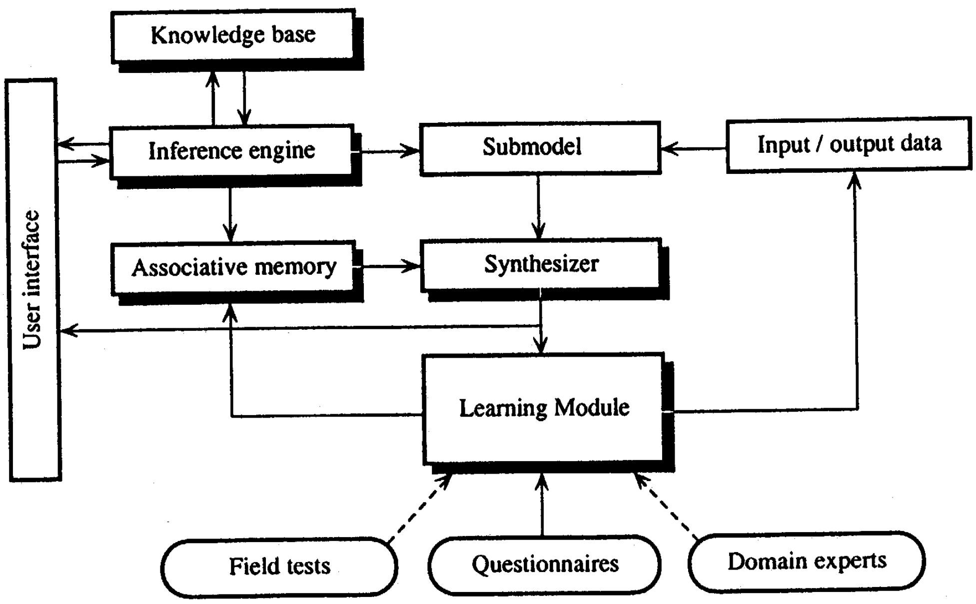

Fig. 7. System Configuration(New System)

engine, the associative memory and the submodels(neural network models) of the system are constructed on a personal computer(NEC PCH98 U100), and the learning module runs on a UNIX workstation (SONY NEWS). The expert system is all written in *C* language.

Fig. 8 illustrates the inference process of this system. Photo 1 shows the startup menu. As a first step, the system asks a series of basic questions for the lowest level subgoals regarding the specifications of the bridge, environmental conditions, traffic volume, the conditions of cracks, etc. and asserts the answers from the user as fact clauses (see Photo 2). Then the system searches all relevant fact clauses according to the inference rules. The system asks new questions if the message number for a found fact clause is "q" and asserts the responses to those questions as new fact clauses. If the found clause has a numeral, the system outputs a corresponding message (see Photo 3). When having found all relevant facts by repeating this forward-chaining inference, the system moves on to the stage of associative memory and neural network inference. First, the associative memory determines the degree of match of the antecedent and calculate the weight for the consequent in the associative memory. The system then combines the outputs obtained here with the outputs from the consequent neural network model to give a diagnosis. The diagnosis given here is actually a set of soundness indicators

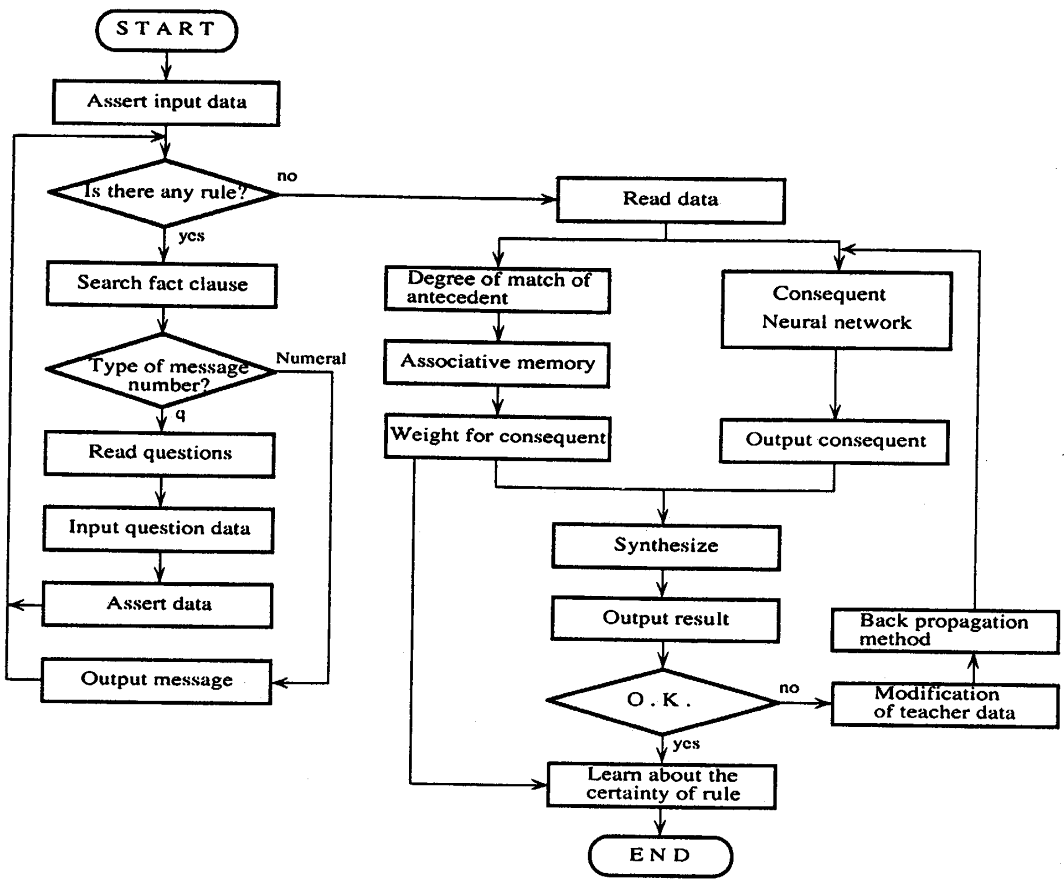

Fig. 8. Inference Process in Inference Engine of the Concrete Bridge Rating Expert System(New System)

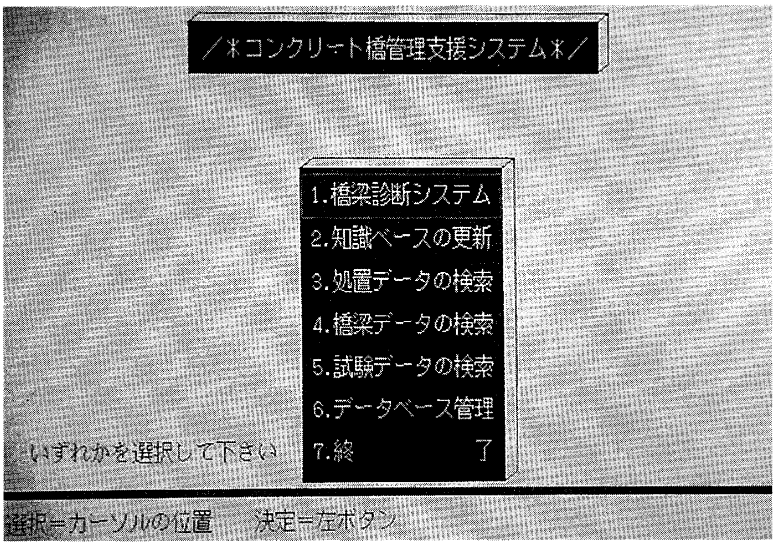

Photo 1. Startup Menu of the Expert System

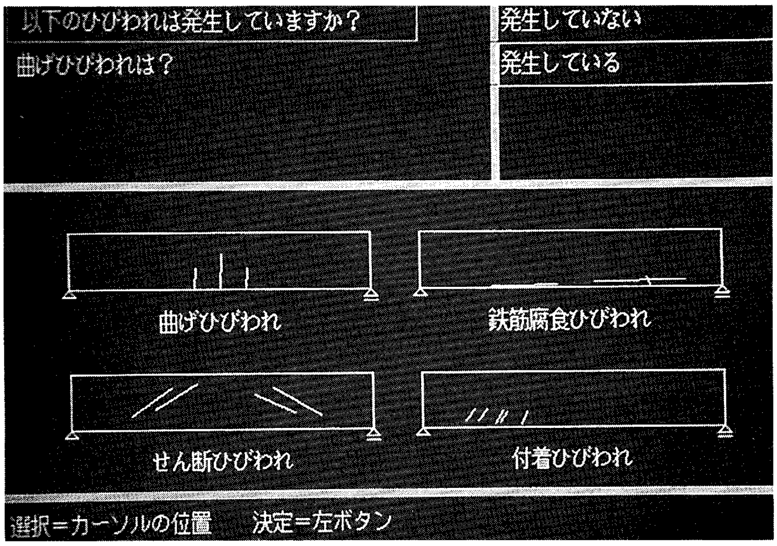

Photo 2. Input Screen

calculated as the probabilities of the five possible conditions, namely, safe, slightly safe, moderate, slightly dangerous, dangerous(see Photo 4). The system can also evaluate bridges with respect to the need for repair or strengthening and the remaining service life of both of the floor slab and the main girder. If a diagnosis is not a proper one, input/output data (teacher data) is modified on the basis of such information as the results of questionnaire surveys so as to refine the knowledge base according to the back propagation algorithm. After that, the neural networks are run again to output a diagnosis reflecting the modification. If the diagnosis is a proper one, the certainty for the corresponding rule is altered and the Concrete Bridge Rating Expert System returns to the startup menu.

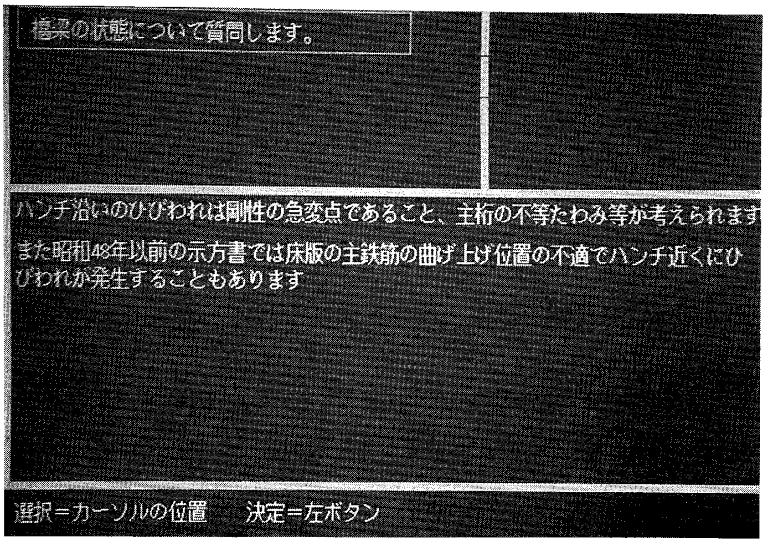

Photo 3. Comment Screen

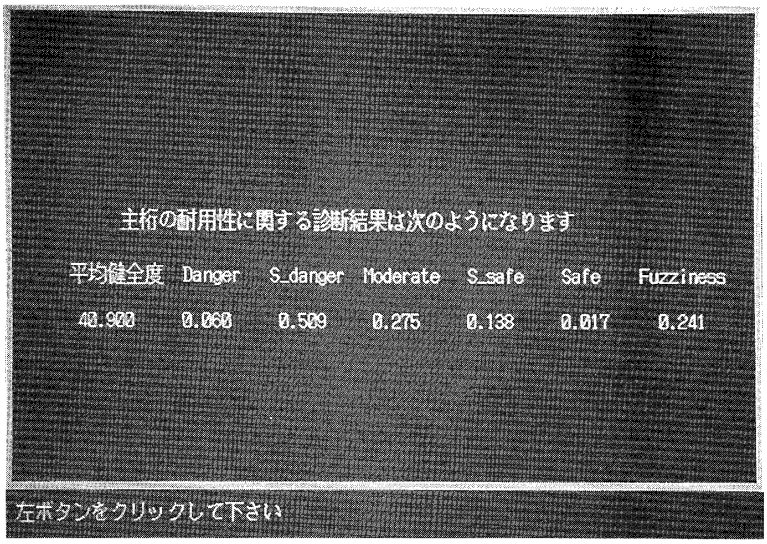

Photo 4. Diagnosis Screen

4. VERIFICATION OF EFFECTIVENESS OF NEURO-FUZZY EXPERT SYSTEM

4.1 Comparison with Previous System[1,2]

The newly developed Concrete Bridge Rating Expert System was used to evaluate the serviceability of an actual bridge. The results of evaluation by this system were compared with results obtained from the previous system to verify the reliability of the acquired initial knowledge.

The bridge evaluated here was a reinforced concrete T-girder bridge[9] that had been constructed with relatively poor execution of work. The main girder then had flexural cracks, shear cracks and cracks due to the corrosion of reinforcing bars. Particularly cracks due to corrosion were rather wide, and water leakage, free lime and spalling of cover concrete around those cracks were noticeable. Tables 1 and 2 show the results of evaluation of the main girder of this bridge by the previous (original) system and the new system. Except for the subgoals for the design of the main girder, the original system and the new system gave similar results(see Tables 1 and 2). With respect to the design of the main girder, since the original system combines membership functions to higher level subgoals following Dempster's rule of combination in the inference process, the degree of uncertainty tends to increase as the inference process progresses. This resulted in the inconsistency of showing two peaks, namely at "slightly dangerous" and "slightly safe" (see Table 1). By contrast, the new system gave results somewhat centering around a single peak (see Table 2). Errors contained in these results need to be corrected through neural network-based learning. In the other respects the results obtained from the original system and the new system showed fair agreement (see Tables 1 and 2).

From above, it can be concluded that the new system has acquired the knowledge of the original system very accurately. Various problems found in diagnoses given by the system[3], however, indicate that the knowledge needs to be refined.

Table 1. Evaluation of RC T-Girder Bridge by Original System

Judgment factor	Mean soundness score	Danger	Slightly danger	Moderate	Slightly safe	Safe
Design	47.0	0.151	**0.273**	0.161	**0.371**	0.044
Execution of work	17.4	0.338	0.605	0.056	0.000	0.000
Service condition	76.0	0.000	0.000	0.167	0.644	0.189
Flexural crack	60.9	0.000	0.173	0.447	0.191	0.189
Shear crack	60.9	0.000	0.186	0.435	0.186	0.194
Corrosion crack	39.6	0.260	0.457	0.016	0.051	0.217
Whole damage of girder	50.9	0.127	0.285	0.293	0.106	0.189
Load-carrying capa. of girder	56.2	0.099	0.185	0.293	0.210	0.213
Durability of girder	49.8	0.146	0.308	0.136	0.244	0.166
Serviceability of girder	51.7	0.161	0.245	0.201	0.221	0.173

Table 2. Evaluation of RC T-Girder Bridge by New System

Judgment factor	Mean soundness score	Danger	Slightly danger	Moderate	Slightly safe	Safe
Design	64.7	0.001	0.019	0.319	**0.564**	0.097
Execution of work	24.8	0.330	0.608	0.055	0.005	0.002
Service condition	70.0	0.014	0.026	0.144	0.575	0.241
Flexural crack	58.4	0.035	0.240	0.260	0.202	0.264
Shear crack	58.7	0.033	0.313	0.145	0.202	0.307
Corrosion crack	25.1	0.283	**0.698**	0.006	0.006	0.007
Whole damage of girder	52.0	0.148	0.222	0.208	0.227	0.195
Load-carrying capa. of girder	65.8	0.001	0.038	0.300	0.493	0.168
Durability of girder	52.6	0.058	0.165	0.394	0.352	0.031
Serviceability of girder	58.9	0.019	0.109	0.343	0.464	0.065

4.2 Refinement of Knowledge Based on Results of Questionnaire Survey

In this section, the refinement of knowledge in the consequent neural network is performed based on teacher data (objective criteria) obtained from questionnaire surveys on domain experts.

As mentioned in Section 3.2, the results of the questionnaire surveys were divided into five categories, each corresponding to 20 points on a scale of 100. These categories were related to the probability of states ranging from dangerous to safe output from the system, and the data thus obtained was used as teacher data (objective criteria). By use of this data, the knowledge was refined according to the back propagation algorithm. Of the evaluation items for the reinforced concrete T-girder bridge mentioned earlier, shown below is the process of knowledge refinement for the subgoals related to cracks in the main girder (see Table 2). Table 3 shows the results of the questionnaire surveys (teacher data) regarding cracks in the main girder. Table 4 shows the results of evaluation by the system after the knowledge refinement of the

Table 3. Example of Teacher Data on Cracks in Girder used for Knowledge Base Refinement

Judgment factor	Danger	Slightly danger	Moderate	Slightly safe	Safe
Flexural crack in girder	0.000	0.154	0.538	0.308	0.000
Shear crack in girder	0.000	0.308	0.231	0.231	0.231
Corrosion crack in girder	0.077	0.154	0.308	0.385	0.077

Table 4. Example of Output after Refinement of Knowledge on Level of Cracks (Girder)

Judgment factor	Mean soundness score	Danger	Slightly danger	Moderate	Slightly safe	Safe
Flexural crack	54.5	0.029	0.179	**0.427**	0.268	0.098
Shear crack	57.6	0.017	0.305	0.208	0.223	0.247
Corrosion crack	51.7	0.090	0.217	0.279	**0.345**	0.070

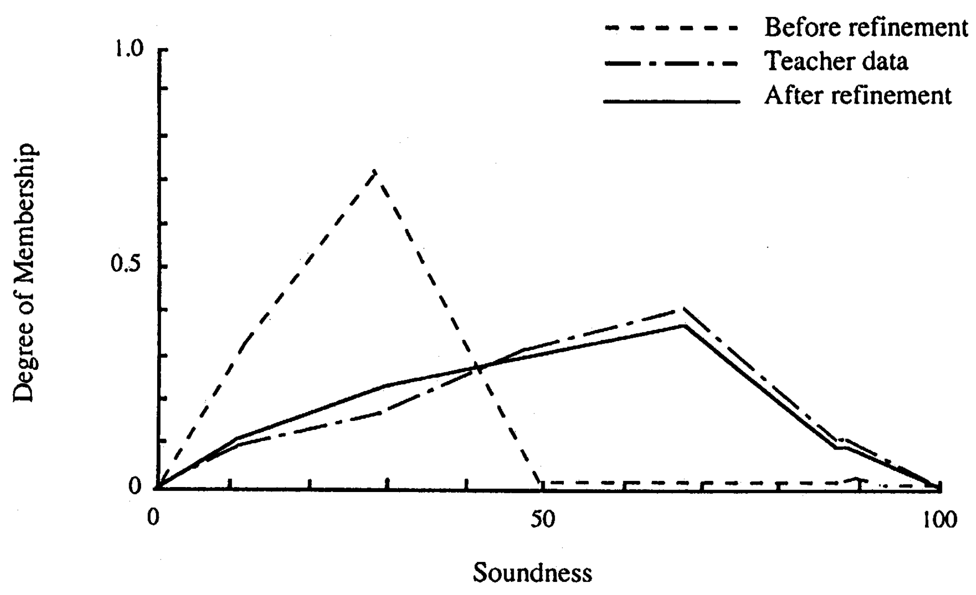

Fig. 9. Comparison of Outputs on Corrosion Cracks in Girder

consequent neural network based on the teacher data shown in Table 3. Figs. 9 and 10 show, in the form of membership functions, the results of evaluation regarding corrosion cracks and flexural cracks in the main girder before the knowledge refinement, the teacher data used in knowledge refinement, and the results of evaluation after the knowledge refinement.

As shown in Tables 2 and 4, and Fig. 9, the corrosion cracks in the main girder were judged "slightly dangerous" before knowledge refinement, while after the knowledge refinement they were judged "slightly safe". As for the flexural cracks in the main girder, the results of evaluation before the knowledge refinement showed more or less

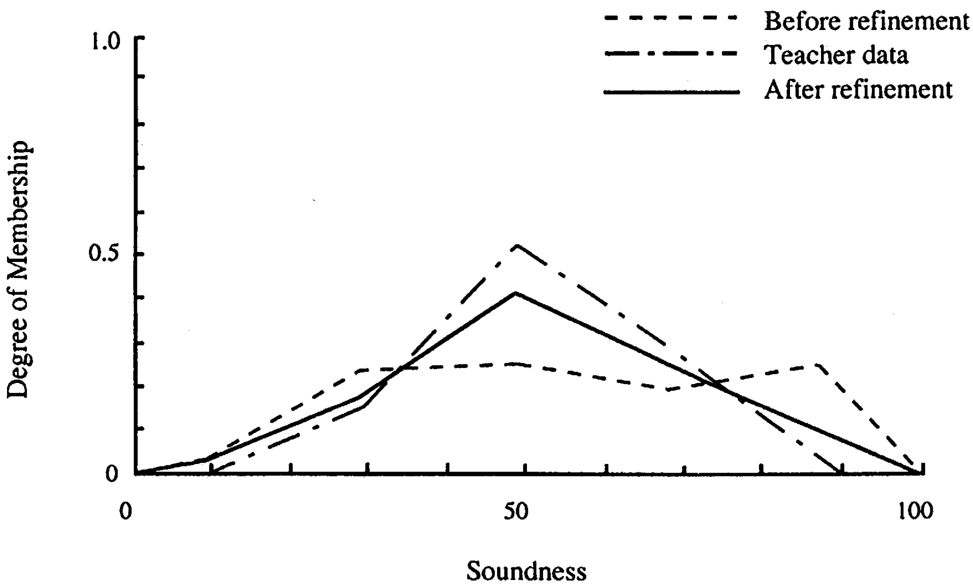

Fig. 10. Comparison of Outputs on Flexural Cracks in Girder

even distribution over the soundness scale, while those after knowledge base refinement shows a peak in the "moderate" range. This indicates that the degree of uncertainty decreased as a result of knowledge refinement (see Tables 2 and 4, and Fig. 10).

From above, it can be concluded that the accuracy of knowledge refinement in this system was considerably high, evidencing the effectiveness of the learning method of the system. In cases, however, where results of questionnaire surveys are used as teacher data (objective criteria), the reliability of the questionnaire results themselves becomes an important consideration. Teacher data might even be inconsistent to the extent of prohibiting knowledge refinement. It is desirable, therefore, that indicators related with more objective data obtained from reliable sources, such as field tests, be used as teacher data.

5. CONCLUSIONS

In this study a Concrete Bridge Rating Expert System with Machine Learning has been developed. Using neural networks, the developed system facilitates the modification of the knowledge base based on data such as results of questionnaire surveys conducted on domain experts. Independent neural networks constructed for individual rules help prevent the inference mechanism from becoming a black box. The time required for learning can also be reduced because the learning process involves only the networks concerned. The results of this study can be summarized as follows:
(1) As a method of refinement of the knowledge base of the Concrete Bridge Rating Expert System, a learning method based on the neural network has been presented. Problems in applying the neural network to the expert system were studied, and an independent network was constructed for each rule in order to help prevent the neural network from becoming a black box.
(2) A new inference process similar to the conventional fuzzy inference has been developed by combining the neutral network and associative memory. The concept of "certainty factor" was introduced so that the certainty factor can be modified automatically depending on the frequency of reference to rules.
(3) The Concrete Bridge Rating Expert System was applied to the girder of an actual bridge to verify the results of evaluation. Good agreement between the results obtained from the original system and the new system confirmed that the knowledge for the new system was successfully acquired from the original system.
(4) The knowledge base was refined using neural networks on the basis of the results of questionnaire surveys on domain experts. Good results achieved as a result of knowledge base refinement evidences the effectiveness of the learning method in the system.
In order to enhance the reliability of the expert system, it is necessary to refine the knowledge base through application to more actual bridges. It is also necessary to clearly define the relationships between the outputs of the system and field data(e.g., linking numerical analysis programs) instead of relying solely on information obtained from visual inspection.

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REFERENCES

1) Miyamoto, A., Kimura, H. and Nishimura, A.: "Expert System for Maintenance and Rehabilitation of Concrete Bridges", Proc. of IABSE Colloquium on Expert Systems in Civil Eng., Bergamo, pp. 207-217, 1989.

2) Miyamoto, A., Masunari, I. and Nishimura, A.: "Development of Expert System for Serviceability Rating of Concrete Bridges and Its Practical Application", J. of the Society of Materials Science, Vol. 40, No. 450, pp.256-262, Nov. 1991.

3) Miyamoto, A., Morikawa, H., Masunari, I. and Furukawa, M.: "A Method of Inductive Machine Learning in Knowledge Base for Bridge Rating Expert System", J. of Structural Engineering, Vol. 37A, II, pp. 643-654, March 1991.

4) Asou, H.: "Information Processing using Neural Network", Sangyo Tosho, 1988.

5) Kosho, B.: "Adaptive Bidirectional Associative Memories", Applied Optics, Vol. 26, No. 23, Dec. 1987.

6) Imasaki, N. and Yamaguchi, T.: "Toward Fuzzy Neural Networks", Computer Today, No. 35, pp. 52-58, Jan. 1991.

7) Yamaguchi, T., Imasaki, N. and Haruki, K.: "Fuzzy Rule Inference/Learning Method Using Associative Memory", IEEE Trans., Japan, Vol. 100-C, No. 3, pp. 207-215, 1990.

8) Kosho, B.(J. S. Denker. Ed.): "Differential Hebbian Learning", Proc. of Amer. Inst. of Physics Conference., Neural Networks for Computing, 1986.

9) The Construction Engineering Research Institute Foundation.: Report on Serviceability Evaluation of the Old Aoki-bashi Bridge, March 1990.