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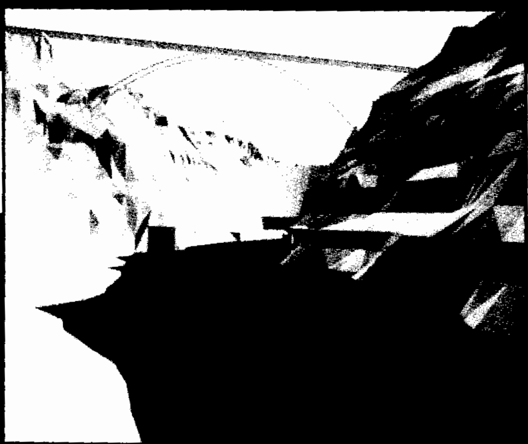

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PROTOTYPE DIAGNOSIS EXPERT SYSTEM WITH KNOWLEDGE REFINEMENT FUNCTION

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ABSTRACT: When developing an expert system, the difficulty in acquiring knowledge poses a bottleneck. It is essential that the system possess a means to modify its knowledge bases. This study details the construction of a versatile inference system equipped with a rule-base refinement function that is expressed by a network with relations between the hypotheses as compositional elements. As an example for practical use, this paper examines the effectiveness of the system being proposed, using the rule base of an existing expert system to diagnose cracks in damaged bridge slabs. As a result, it was found that, by presenting adequate examples as training samples, the rule base is refined along with a remarkable increase in damage-cause inference accuracy.

INTRODUCTION

In the field of civil engineering, many expert systems have been developed with learning functions to modify knowledge bases. For example, Miyamoto et al. (1991) proposed a method to refine knowledge by changing the membership function in a fuzzy expert system used for diagnosis of a concrete bridge. In addition, Kushida and Miyamoto (1995) proposed a knowledge modification method in which the degree of refinement was considered by introducing the concepts of possibility or necessity.

Mikami et al. (1992a) constructed an expert system with a causal network for selecting a method of retrofitting steel bridges that were damaged by fatigue. They added a learning function to the system using neural networks (Mikami et al. 1994), then acquired rules in the knowledge base by automatically generating undefined causal relations (Mikami et al. 1992b). Tanaka et al. (1995, 1996) also constructed a system in which rule-based and case-based reasoning were used simultaneously. A case-based approach was used to design and optimize steel frames under various load conditions, based on examples of optimal designs by Arciszewski and Ziarko (1991). By combining multimedia and case-based reasoning technology, Mather and Balachandran (1994) developed a prototype case-based system to assist structural designers in the conceptual design stage. Reich et al. (1996) reported on the use of machine learning programs for modeling engineering decision-making procedures. When attempting to use a commercial machine learning tool as a means of knowledge acquisition in addition to explicit domain extraction, Melhem et al. (1996) found that such a tool was not necessarily effective because inductive learning requires the availability of a large database on cases of error.

As described above, various knowledge-acquisition methods have been developed beginning with typical methods such as questionnaires (Cohn et al. 1988). Conversely, the expert systems constructed until now employ a wide variety of knowledge expression methods. From the standpoint of sharing or reusing knowledge, it is also very important to establish a methodology theory that makes it possible to easily reconstruct a rule base that accurately reflects the inference results by using existing systems.

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With this situation in mind, this study proposes an algorithm that refines the rule base by presenting the inference results of existing systems as training samples. By so doing, it is possible to construct a rule-base inference system that is approximately equivalent to that of existing systems. Thus, not only is it possible to easily and explicitly obtain the intensity of the causal relation coincident with the cases given as training samples, but the proposed algorithm can also be developed into an integration of multiple rule-base systems. The algorithm is applied, as an example of practical use, to the rule base for inferring the cause of damage to a road bridge that has a reinforced concrete floor system (Mikami et al. 1988). Thus the effectiveness of this algorithm is examined.

PROPOSED EXPERT SYSTEM WITH KNOWLEDGE REFINEMENT FUNCTION

Numerical Expression of Hypotheses and Relations among Hypotheses

In the inference system presented in this study, a network composed of nodes and linkages describes the hypotheses and relations among the hypotheses, respectively. The node attributes (hereafter called nodal values) indicate the possibility that the hypotheses are valid, whereas the linkage attributes (hereafter called weights) indicate the respective intensities of the relations among the hypotheses. These attributes are expressed with real number values in the range of [0, 1]. In addition, certainty factors are endowed with nodal values and weights, called the nodal certainty factors and rule certainty factors, respectively. Conversely, the respective nodes can possess training samples that are obtained from past cases. The training samples possess nodal training sample values and nodal training certainty factors as attributes.

Inference Algorithm

Fig. 1 shows a schematic diagram of the overall composition of the inference system proposed in this paper. It is assumed that individual rules are allowed to have two or more condition parts. For example, i_1, i_2, and i_3 indicate the condition parts of the ith rule. The i_0 node indicates the conclusion part of this rule. The ith rule has weight w_i and rule certainty factor $c_{w,i}$ as attributes. Conversely, for every individual rule i, each node il (l = 1, 2, 3, . . .) has a nodal value a_{i_l} and a nodal certainty factor c_{i_l}. In the example shown in Fig. 1, the ith, jth, and kth rules reach the same conclusion. Output nodes (conclusions) of a rule can also be input nodes (conditions) for one or more other rules.

A nodal value of an output node (conclusion) is calculated by minimum operation applied to nodal values of the input nodes (conditions) and weights of the corresponding rule as follows:

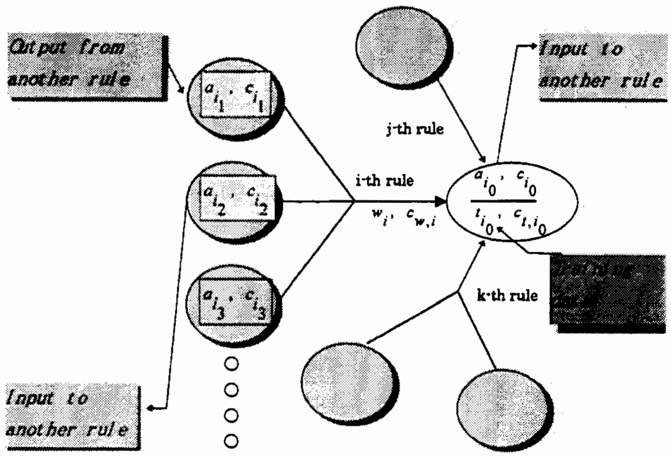

FIG. 1. Schematic Diagram of Proposed Inference System

$$\bar{a}_i = \wedge\left(\underset{l}{\wedge} a_{i_l},\ w_i\right) \tag{1}$$

The corresponding certainty factor of this conclusion is also calculated using the certainty factors of the input nodes (conditions) as follows:

$$\bar{c}_i = c_{i_{\bar{l}}} \cdot c_{w,i} \tag{2}$$

where $c_{i_{\bar{l}}}$ = nodal certainty factor that corresponds to the node selected by the minimum operation done in the parenthesis of (1).

If the node is the conclusion part for only a single rule, values obtained by (1) and (2) are directly adopted as the nodal value and nodal certainty factor of the conclusion part according to the following relations:

$$a_{i_0} = \bar{a}_i \tag{3}$$

$$c_{i_0} = \bar{c}_i \tag{4}$$

On the other hand, if the node is the conclusion part for two or more rules, the values obtained from (1) and (2) are combined as follows to evaluate the nodal value and nodal certainty factor for the conclusion part:

$$a_{i_0} = \underset{m}{\vee}(\bar{a}_m) \tag{5}$$

$$c_{i_0} = \dot{+}(c_m) \tag{6}$$

where $\dot{+}$ indicates $a \dot{+} b = a + b - a \cdot b$; and $\dot{+}(c_m)$ indicates that $c_{m_1} \dot{+} c_{m_2}\ \forall\ m_1, m_2 \in m$.

Refinement Algorithm

As shown in Fig. 1, the individual nodes have training data. The training data have pairs of values t_{i_0} and certainty factors c_{t,i_0} as attributes. Inference is performed when the nodal training certainty factor is smaller than the rule certainty factor. Conversely, the rule base is modified when the rule certainty factor is smaller than the nodal training certainty factor.

The difference between the nodal value and the nodal training value, and between the nodal certainty factor and the nodal training certainty factor, are calculated as follows:

$$\Delta a_{i_0} = a_{i_0} - t_{i_0} \tag{7}$$

$$\Delta c_{i_0} = c_{i_0} - c_{t,i_0} \tag{8}$$

If (8) results in a positive value, the nodal training value and nodal training certainty factors are modified as follows:

$$t_{i_0} \leftarrow t_{i_0} + \eta \cdot \Delta a_{i_0} \tag{9}$$

$$c_{t,i_0} \leftarrow c_{t,i_0} + \eta \cdot \Delta c_{i_0} \tag{10}$$

where η = learning ratio that is to be determined by trial and error.

If (8) results in a negative value, the following procedure is applied: Let $\bar{m}$ be the rule number that has been adopted for maximum operation shown by (5) and $a_{\bar{m}\bar{l}}$ be the nodal value that has been adopted for minimum operation shown by (1), then the nodal value and certainty factor given to that node are modified as follows:

$$a_{\bar{m}\bar{l}} \leftarrow a_{\bar{m}\bar{l}} + \eta \cdot \Delta a_{i_0} \tag{11}$$

$$c_{\bar{m}\bar{l}} \leftarrow c_{\bar{m}\bar{l}} + \eta \cdot |\Delta c_{i_0}| \tag{12}$$

In the above case (i.e., Δc_{i_0} is negative), if the weight of the rule has been adopted for minimum operation, the weight and rule certainty factor are modified as follows:

$$w_{\bar{m}} \leftarrow w_{\bar{m}} + \eta \cdot \Delta a_{i_0} \tag{13}$$

$$c_{w,\bar{m}} \leftarrow c_{w,\bar{m}} + \eta \cdot |\Delta c_{i_0}| \tag{14}$$

Inference starts from the node corresponding to known a priori information based on observation or experience. With the node having input, inference is made when information from all items of input are in alignment using (1)–(6) and successively continues to linkage on the downstream flow side. If all the rules are applied and the downstream flow reaches nodes that do not have any output node, the individual attributes of the node or rule are modified using the inference algorithm shown by (7)–(14). This process is repeated until individual attributes can no longer be changed. At this state refinement of the rule base is considered complete.

APPLIED RULE BASE

The rule base to which the proposed algorithm is applied is a damage-cause-estimation expert system to a road bridge that has a reinforced concrete floor system (Mikami et al. 1988) (hereafter called Mikami's system). As shown in Fig. 2, an estimate of the cause of damage is based on the type of damage inferred from the type of visible damage, lane of traffic, applied design code, and location of damage. Tables 1 and 2 list the types of damage and the causes of damage, respec-

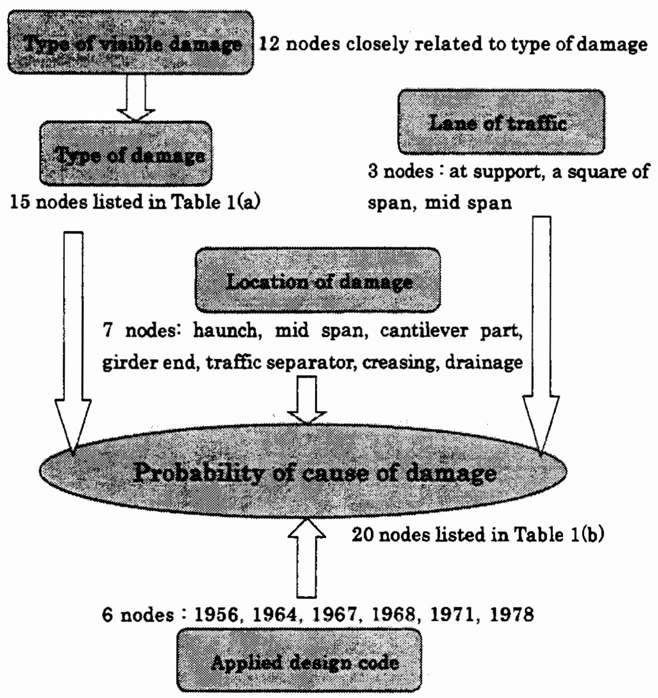

FIG. 2. Diagnosis Expert System by Mikami et al. (1988)

TABLE 1. Type of Damage (Mikami et al. 1988)

Type of damage (1)	Number (2)
Crack	
Lengthwise	13
Crosswise	14
Lengthwise and crosswise	15
Lattice	16
Random	17
Passing through	18
Striping of surface concrete	
Rising of surface	19
Striping of covering concrete	20
Failure	21
Free lime	22
Linkage of water	23
Exposure of reinforcement	
Insufficient covering for reinforcement	24
Striping of surface concrete	25
Rust	
Rusty reinforcement	26
Corrosion	
Corrosion of reinforcement	27

Note: Visible damage closely related to type of damage is numbered from 1 to 12.

TABLE 2. Cause of Damage (Mikami et al. 1988)

Cause of damage (1)	Number (2)
Load	
Excessive traffic load	28
Impact load	29
Relation between lanes of traffic and girder arrangement	30
Design or structural	
Insufficient stiffness caused by thin slab	31
Insufficient stiffness caused by inadequate reinforcement	32
Insufficient distribution bars	33
Insufficient reinforcement caused by inadequate bending position	34
Tensile stress caused by drying shrinkage and constraints imposed by main giders	35
Additional bending moment caused by nonuniform settlement	36
Tensile stress caused by negative bending moment of slab	37
Presence of load distribution cross beam	38
Construction	
Low quality of concrete material	39
Freezing caused by placement in winter	40
Insufficient curing	41
Insufficient work on construction joint	42
Error in reinforcement arrangement	43
Insufficient covering for reinforcement	44
Others	
Freezing and thawing	45
Salt	46
Drainage from slab surface	47

tively. Table 3 lists the input information presented to the system as eight training cases.

As an example, Table 4 lists the causal relations between the causes of damage and types of damage at haunches. The symbols ◎, ○, and △ indicate certainty factors of 0.5, 0.3, and 0.1, respectively. Mikami et al. (1988) proposed that three such classes should be adequate. In calculating the certainty factor of each conclusion, a method adopted in the MYCIN system (Buchanan and Shortliffe 1984) was employed.

In this study, values of 3/4, 2/4, and 1/4 are individually provided as weights of the rule corresponding to the certainty factors on the rule base of Mikami's system. The weights are very large compared to the certainty factors given by Mikami et al. (1988), because inference is performed by minimum-maximum operation. There are 63 total hypotheses and 872 rules. Moreover, Table 5 lists results from inference made for the cases in Table 3 using Mikami's system. The numbers 28 to 47 in the table correspond to numbers of each cause of damage in Table 2.

INFERENCE ON CAUSE OF DAMAGE BEFORE REFINEMENT OF RULE BASE

Cause of damage was first inferred by using the rule base as secured information. Fig. 3 shows an example of the inference results for Case 1. In this figure, the abscissa indicates the node numbers of the cause of damage and the ordinate indicates the probability of cause of damage. The figure also shows the probability of cause of damage inferred by Mikami's system.

Fig. 4 shows the differences between the possibility inferred by Mikami's system and those given by the writers' system, which are defined as follows:

$$\text{error} = \frac{\sum_i |t_i - a_i|}{n} \tag{15}$$

where t_i indicates a possibility of the ith damage cause obtained by Mikami's system; a_i indicates the possibility of the ith damage cause obtained by the writers' system; and n represents the number of damage causes targeted as objectives. Differences in inference results between Mikami's system and the proposed system are mainly due to the possible nonexistence of distinct foundation weights of 3/4, 2/4, and 1/4 used in transferring the rule based constructed by Mikami et al. (1988). Relatively good coincidence is seen, however, with regard to how large the probability of cause of damage is in each case.

INFERENCE ON CAUSE OF DAMAGE AFTER REFINEMENT OF RULE BASE

By presenting the inference results of Mikami's system, which are regarded as established information, the rule base was modified. Then the probability of cause of damage was inferred by using the modified rule base. To prevent the training samples from being changed, all nodal training certainty factors were assumed to be 1.0 and all rule certainty factors were taken to be 0.1. The rule certainty factors after modifying were also used in inferring the possibility of cause of damage. The nodal values and nodal certainty factors were respectively assumed to be 0.5 and 0.1 because the possibility of cause of damage was considered to be unknown information in this case.

Rule Refinement Using Each Case as Training Sample

Training data for Cases 1–8 were presented individually and the rule base was modified. Fig. 4 includes the differences between the possibility inferred by Mikami's system and the possibility in this case. Fig. 5 shows two selected cases of the inference results. The possibility of damage causes is given on the ordinate for Cases 2 and 4. For comparison, the training sample is also shown.

Because this inference system was originally based on learning with training samples, the inference results must match training sample data when a case is presented as the training sample and the inference system is applied to the case. However, modifying rules using individual cases is tantamount to obtaining different rules for each case, whereas the objective of this study is to obtain only one rule base associated with all training samples. Therefore, the rule base is modified using multiple cases as training samples, as in the next paragraph.

TABLE 3. Cases Used as Training Samples (Mikami et al. 1988)

Damage (1)	Case Number 1 (2)	2 (3)	3 (4)	4 (5)	5 (6)	6 (7)	7 (8)	8 (9)
Visible damage								
Crack	Lengthwise and crosswise	Lengthwise and crosswise	Lengthwise and crosswise	Lengthwise and crosswise	Lengthwise and crosswise	Lengthwise and crosswise	Lengthwise and crosswise	Lengthwise and crosswise
Splitting	—	—	—	—	—	—	—	—
Impurity	Free lime	Free lime	Free lime	Free lime	Free lime	Water leakage	—	—
Location of damage	Haunch	Mid span	Girder end	Haunch	Haunch	Haunch	Haunch	Haunch
Design code	March 1964	March 1964	March 1964	Sep. 1967	Feb. 1980	March 1964	March 1964	March 1964
Passing position of traffic load	Quarter of span	—	—	Quarter of span	Quarter of span	Quarter of span	Quarter of span	Quarter of span

TABLE 4. Relationship between Cause of Damage and Type of Damage at Haunches (Mikami et al. 1988)

Cause of damage (1)	Type of Damage 13 (2)	14 (3)	15 (4)	16 (5)	17 (6)	18 (7)	19 (8)	20 (9)	21 (10)	22 (11)	23 (12)	24 (13)	25 (14)	26 (15)	27 (16)
Loads															
28	○	△	○	○	○	○	○	○	◎		○		◎		
29	△	○	○	○	○	○	○	○	○		△		○		
30															
Design or structural															
31	○	○	◎	◎	◎	◎	○	○	◎	○	◎		◎		
32	◎	○	◎	◎	◎	◎	○	○	◎	○	○		◎		
33	◎	◎	◎	◎	◎	◎	○	○	○	◎	◎		○		
34	◎	△	◎	◎	◎	◎	○	○	◎		○		◎		
35											○				
36		○	○	○	○	○									
37		○	○	○	○	○			○	○	△				
38		○	○	○	○	○			△	△	△				
Construction															
39	△	△	△	△	△	△	△	△	△		△		△	△	△
40	△	△	△	△	△	△	△	△	△		△		△	△	△
41	△	△	△	△	△	△	△	△	○		△		△	△	△
42		△	△	△	△	△	○	○	○	○	○	○	○	○	○
43	△	△	△	△	△	△	△	△	△			○	○	○	○
44		△	△	△	△	△	○	○	○			◎	◎	○	○
Others															
45		△	△	△	△	△									
46													△	○	○
47					△	△			△	◎	◎		△	○	○

Note: Numbers from 13 to 27 in first row are identical to those shown in Table 1, and numbers from 28 to 47 in first column are identical to those shown in Table 2.

TABLE 5. Inference Results Obtained Using Mikami's System

Case (1)	Cause 28 (2)	29 (3)	30 (4)	31 (5)	32 (6)	33 (7)	34 (8)	35 (9)	36 (10)	37 (11)	38 (12)	39 (13)	40 (14)	41 (15)	42 (16)	43 (17)	44 (18)	45 (19)	46 (20)	47 (21)
1	0.73	0.73	0.92	0.9	0.88	0.92	0.85	0.4	0.71	0.77	0.74	0.32	0.32	0.32	0.55	0.38	0.38	0.24	0.18	0.58
2	0.9	0.77	0.5	0.73	0.73	0.6	0.3	0.4	0.59	0.65	0.6	0.4	0.52	0.56	0.58	0.1	0.2	0.1	0	0.05
3	0.86	0.86	0.47	0.76	0.86	0.85	0.3	0.33	0.31	0.31	0.31	0.37	0	0.5	0	0.48	0.54	0	0	0.75
4	0.73	0.73	0.92	0.9	0.88	0.89	0.85	0.4	0.71	0.77	0.74	0.32	0.32	0.32	0.55	0.38	0.38	0.24	0.18	0.58
5	0.73	0.73	0.92	0.85	0.83	0.89	0.78	0.16	0.59	0.77	0.63	0.32	0.32	0.32	0.55	0.38	0.38	0.24	0.18	0.58
6	0.73	0.73	0.9	0.88	0.86	0.9	0.85	0.4	0.72	0.73	0.73	0.32	0.32	0.32	0.48	0.38	0.38	0.24	0.18	0.45
7	0.72	0.72	0.88	0.85	0.85	0.86	0.85	0.3	0.68	0.68	0.68	0.25	0.25	0.25	0.35	0.27	0.35	0.2	0.35	0.18
8	0.53	0.53	0.65	0.65	0.65	0.65	0.65	0.3	0.53	0.53	0.53	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0	0.05

Rule Refinement Using Multiple Cases as Training Samples

All Cases Are Presented Simultaneously

One method of modifying the rule base is to present all eight training cases simultaneously. Then the probability of cause of damage complying with individual cases can be inferred. Fig. 5 shows the inference results obtained this way, as well as the inference results of Mikami's system and the results when that individual case is presented. Fig. 4 includes the differences between the possibility inferred by Mikami's system and the possibility in this case.

It was found that the ratio that coincides with the individual training samples was lowered when the rule base modified by simultaneously presenting all cases. Despite the fact that inference accuracy for individual cases is lower, mainly because the rule base is modified for obtaining a single rule base, the error is marginal, with the results shown in Figs. 4 and 5.

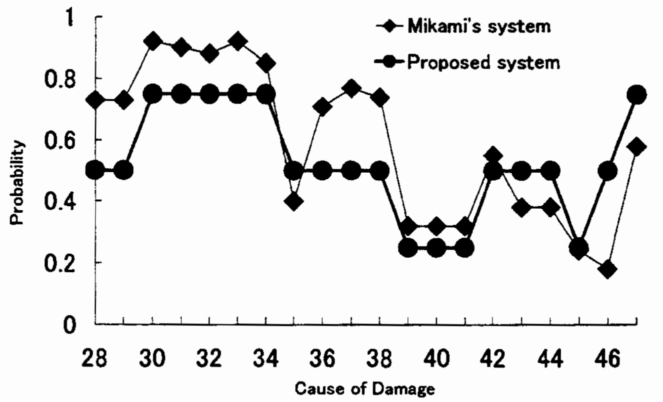

FIG. 3. Probability of Cause of Damage for Case 1 (before Rule Refinement)

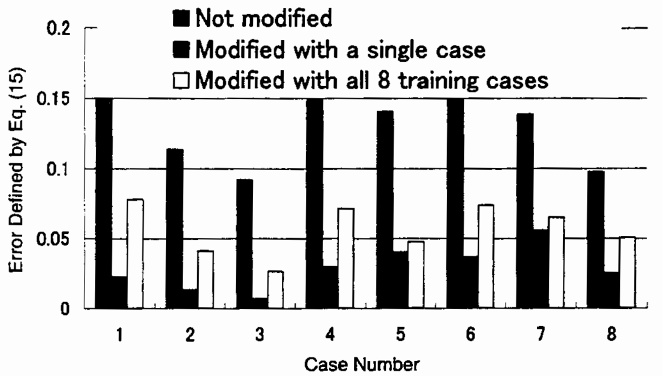

FIG. 4. Difference between Training Samples and Inference Results Defined by Eq. (15)

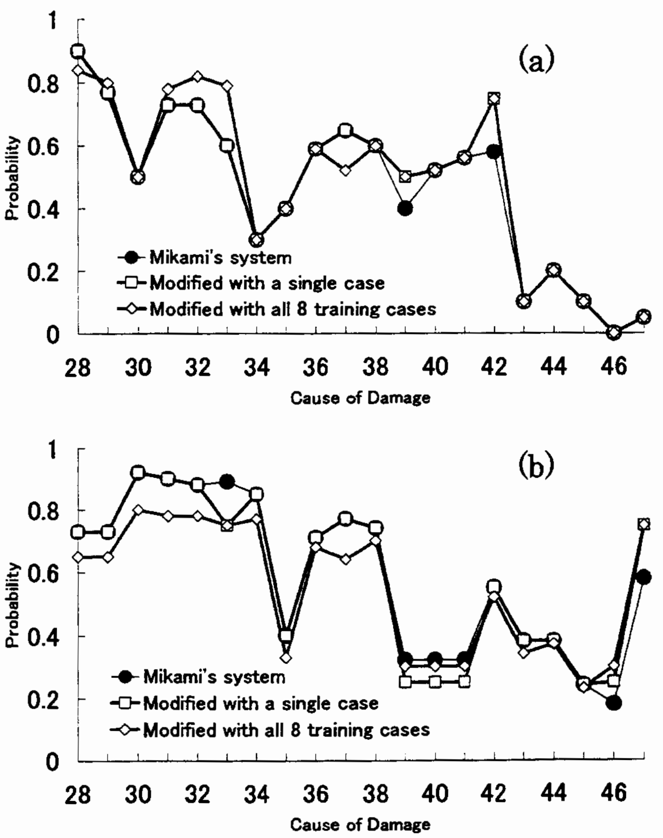

FIG. 5. Probability of Cause of Damage: (a) Case 2; (b) Case 4

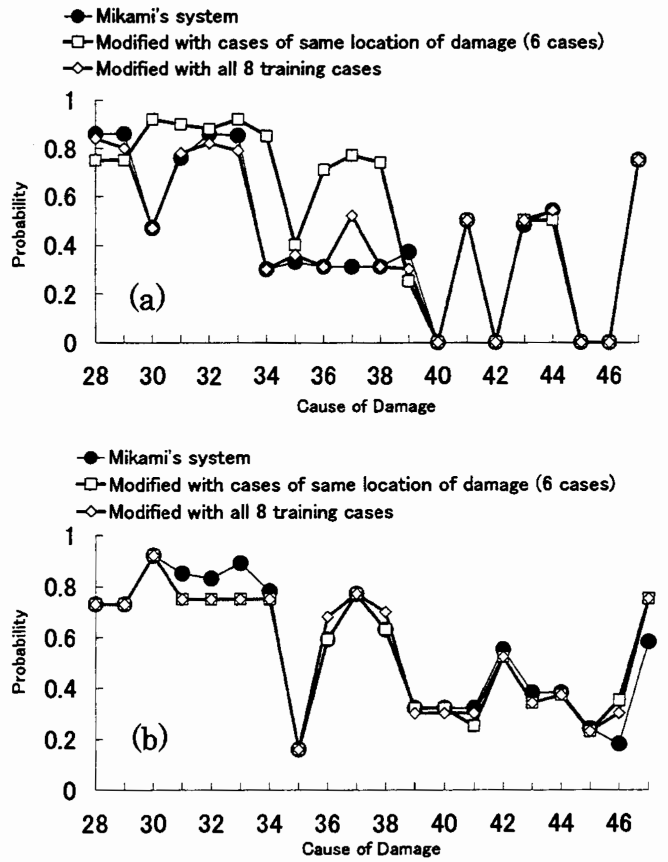

FIG. 6. Probability of Cause of Damage: (a) Case 3; (b) Case 5

Cases Damaged at Same Location Are Presented Simultaneously

Table 3 shows that the location of damage in Cases 1 and 4–8 was "damage at haunches." Then the rule base was modified by presenting these six cases simultaneously. As an example, Fig. 6 shows the inference results for Cases 3 and 5. In this figure, the results (with which eight cases are presented simultaneously) and training samples are shown concurrently for the sake of comparison.

It is clear that the degree of coincidence with the training sample for Case 5 has not changed, whereas errors increased significantly in the inference results for Case 3, whose inference result was not presented as a training sample. This result implies that the relationship between the cause of damage and the type of damage is largely affected by the location of damage and that training samples for modifying the rule base should be carefully selected.

CONCLUSIONS

The principal conclusions obtained from this study are listed below:

- When the probability of cause of damage is inferred by taking the rule base as established information, classification is enabled by using possible damage causes as training samples.
- When the rule base is modified by presenting the inference results of an existing system as established training cases to be followed by inference of the damage cause using the rule-base refinement algorithm.
- If the rule base is modified presenting individual training cases, the inference results of individual cases are almost coincident with the training samples.
- When all multiple cases are presented simultaneously,

there is no significant deterioration in inference accuracy compared to when individual cases are presented.

- In inference for cases that are not presented as training samples, training sample data for modifying the rule base must be carefully selected.

As described above, using the method proposed in this paper makes it possible to construct a rule-base system having inference performance matching that of an existing system. Provided that the cases are properly selected, it is possible to secure the inference accuracy of cases not presented. Constructing a system with the functions of multiple rule-base systems and planning to share and reuse knowledge acquired by this system are designated as future projects.

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APPENDIX I. REFERENCES

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APPENDIX II. NOTATION

The following symbols are used in this paper:

a_{i_l} = nodal value of lth node for ith rule;
a_{i_0} = nodal value of conclusion part for ith rule;
c_{i_l} = certainty factor of nodal value of lth node for ith rule;
c_{i_0} = nodal certainty factor of conclusion part for ith rule;
c_{t,i_0} = certainty factor of training data of conclusion part for ith rule;
$c_{w,i}$ = certainty factor of weight for ith rule;
t_{i_0} = training data of conclusion part for ith rule;
w_i = weight for ith rule;
Δa_{i_0} = modification value of a_{i_0};
Δc_{i_0} = modification value of c_{i_0};
η = learning ratio;
$\forall$ = "for all";
$\wedge$ = minimum operation;
$\vee$ = maximum operation; and
$\leftarrow$ = "is replaced by."