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A DIAGNOSIS EXPERT SYSTEM ATTACHED WITH KNOWLEDGE REFINEMENT FUNCTION

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ABSTRACT: This study proposes the algorithm to refine the rule base by presenting the inference results of the existing knowledge-base system as training samples after the inference system was composed by means of a versatile mutual linkage network. By so doing, rule base inference which is almost the same as the existing system becomes possible, and it is not only possible to obtain very easily in an explicit style the strength of the causal relation which will be coincident with the cases shown as training samples, but also possible to allow the strength to develop into the unification of plural rule base systems. The proposed algorithm is applied, as an example for practical use, to the rule base for the purpose of inferring the damage cause of the road bridge RC floor system developed by Mikami, Tanaka, et al., to which the influence caused by the presentation method of the training samples to refine the rule base. Thus the effectiveness of this system was examined.

KEYWORDS: expert systems, knowledge acquisition, case base, diagnosis, network systems

1.INTRODUCTION

Expert systems that have been constructed to now employ a wide variety of knowledge expression methods, and it is very important, from a point of view of sharing knowledge or reusing it , to establish a methodology theory making it possible to reconstruct the rule base reflecting very easily the inference results by means of the existing system [1,2,3].

Keeping such a situation in mind, this study proposes the algorithm to refine the rule base by presenting the inference results of the existing system as training samples after the inference system was composed by means of a versatile mutual linkage network with the rule base. By so doing, rule base inference which is almost the same as the existing system becomes possible, and it is not only possible to obtain very easily in an explicit style the strength of the causal relation which will be coincident with the cases shown as training samples, but also possible to allow the strength to develop into the unification of plural rule base systems. The proposed algorithm is applied, as an example for practical use, to the rule base for the purpose of inferring the damage cause of road bridge RC floor systems developed by Mikami, Tanaka, et al. [4]. Thus the effectiveness of this system was examined.

2.PROPOSED SYSTEM

2.1 NUMERICAL EXPRESSION OF HYPOTHESES AND RELATIONS AMONG HYPOYTHESES

In the inference system constructed in this study, the node composing the network and the linkage

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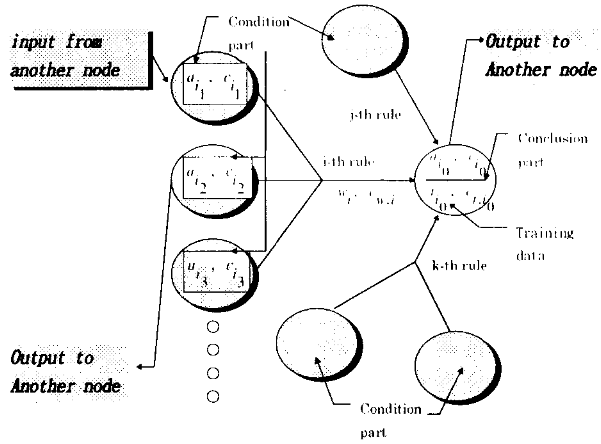

Fig. 1. Schematic Diagram of the Inference System Proposed

show respectively the hypotheses and the relation between the hypotheses. The attributive values of these degrees are the possibility that the hypotheses are formed, which are hereafter called node values, and the strength of the relation between the hypotheses, which are hereafter called linkage coefficients. These are expressed with the real number values of the interval [0,1]. Furthermore certainty degrees are endowed with the node values and linkage coefficients, and the certainty degrees thus provided are called the node certainty degrees and rule certainty degrees, respectively. On the other hand, the respective nodes can possess the training samples obtainable from the cases in the past. The training data possess the [node training sample value, node training certainty degree] as attributive values corresponding to the [node value, node certainty degrees] as the attributive values of the individual hypotheses.

2.2 INFERENCE ALGORITHM

Fig. 1 illustrates a schematic diagram of the whole composition of the inference system in question. On the assumption that the individual rules are allowed to have plural condition parts, the nodes such as i_1, i_2, i_3, etc. indicate the condition part of the i-th rule. Meanwhile the i_0 node indicates the conclusion part of the same rule. The i-th rule is defined by the linkage coefficient w_i and rule certainty factor $c_{w,i}$. On the other hand, let it be understood that the individual rules are defined by the node value a_{il} and node certainty factor c_{il}. Hereunder shown is the inference algorithm using these attributive values.

First of all, let the node value and the certainty factor directed from a rule be obtained in accordance with the so-called minimum-operation in the equations (1) and (2), respectively.

$$\bar{a}_i = \wedge\left(\wedge_l a_{i_l}, w_i\right) \quad (1) \qquad \bar{c}_i = c_{i_l} \cdot c_{w,i} \quad (2)$$

In the event that the node is the conclusion part of only a single rule, the values obtained by the equations (1) and (2) become the node value and node certainty degree of the conclusion part. In the event that a node is the conclusion part of more than two rules, let the values obtained from the those equations be unified with respect to these rules using the equations (3) and (4) shown below, and furthermore let the node value and node certainty degree of the conclusion part be obtained.

$$a_{i_0} = \vee\left(\bar{a}_m\right) \qquad (3) \qquad\qquad c_{i_0} = \dot{+}\left(\bar{c}_m\right) \qquad (4)$$

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

2.3 REFINEMENT ALGORITHM

By comparing the node certainty degree of the conclusion part of the i-th rule obtained by inference with the training certainty degree given to the same node, let the node certainty value or the node value with lower node training certainty degree be renovated. First of all, let the differences between node value and the node training value and between the node certainty degree and the node training certainty degree be obtained in accordance with the equations (5) and (6) shown below.

$$\Delta a_{i_0} = a_{i_0} - t_{i_0} \qquad (5) \qquad\qquad \Delta c_{i_0} = c_{i_0} - c_{t,i_0} \qquad (6)$$

In the event that the training data are regarded as the information with a lower certainty degree provided that $\Delta c_{i_0} \geq 0$, the node training value and node training certainty degree are renovated in accordance with the equations (7) and (8).

$$t_{i_0} \leftarrow t_{i_0} + \eta \cdot \Delta a_{i_0} \qquad (7) \qquad\qquad c_{t,i_0} \leftarrow c_{t,i_0} + \eta \cdot \left|\Delta c_{i_0}\right| \qquad (8)$$

where n is a learning ratio. In the event that $\Delta c_{i_0} < 0$, and provided that what is adopted in the minimum-maximum operation in the executed inference is the node value of the m_l-th node corresponding to the condition part of the m-th rule, the node value and node certainty degree corresponding to the said node are renovated using the equations (9) and (10) shown below.

$$a_{\bar{m}_l} \leftarrow a_{\bar{m}_l} + \eta \cdot \Delta a_{i_0} \qquad (9) \qquad\qquad c_{\bar{m}_l} \leftarrow c_{\bar{m}_l} + \eta \cdot \left|\Delta c_{i_0}\right| \qquad (10)$$

Meanwhile provided that what is adopted by means of the min-max operation is a linkage coefficient of the m-th rule, the linkage coefficient and rule certainty degree of the said rule are renovated using the equations (11) and (12).

$$w_{\bar{m}} \leftarrow w_{\bar{m}} + \eta \cdot \Delta a_{i_0} \qquad (11) \qquad\qquad c_{w,\bar{m}} \leftarrow c_{w,\bar{m}} + \eta \cdot \left|\Delta c_{i_0}\right| \qquad (12)$$

3. APPLIED RULE BASE

The rule base applied is the damage-cause-estimation expert system of the road bridge RC floor system developed by Mikami, Tanaka, et al. (hereafter called existing system)[1]. The existing system is for checking to see from the state of the road bridge RC floor system what was the cause of the damage. To be concrete with this, the estimation of the damage cause is made by obtaining the types of the damage from the visible damage taking into account the obtained types of the damage, passing position of the traffic loads, applied specifications, and places of the damage. The damage cause taken up as objectives for the estimation are listed in Table 1. Furthermore kinds of the input information presented for the existing system are listed in Table 2.

Table 1. Damage Causes Taken up as Objectives for Estimation[4]

	#	Damage cause
Loading	28	Excessive traffic loads
	29	Impact loading
	30	Relation between passing position of traffic loads and girder arrangement
Design or Structural	31	Insufficient stiffness caused by thin slab
	32	Insufficient stiffness caused by inadequate reinforcement
	33	Insufficient distribution bars
	34	Insufficient reinforcement caused by inadequate bending position
	35	Tensile stress caused by drying shrinkage and constraints by main girders
	36	Additional bending moment caused by non-uniform settlement
	37	Tensile stress caused by negative bending moment of slab
	38	Presence of load distribution cross beam
Construction	39	Low quality of concrete material
	40	Freezing caused by placing in Winter
	41	Insufficient curing
	42	Insufficient work of construction joint
	43	Error of reinforcement arrangement
	44	Insufficient covering for reinforcement
Others	45	Freezing and melting
	46	Salt
	47	Drainage from the slab surface

Table 2. Cases used as training samples.[4]

		Case #1	Case #2	Case #3	Case #4
Visible damage	Crack	Lengthwise and crosswise	Lengthwise and crosswise	Lengthwise and crosswise	Lengthwise and crosswise
	Splitting	-	-	-	-
	Impurity	Free lime	Free lime	Free lime	Free lime
Place of damage		Haunch part	Mid span	Girder end	Haunch part
Design code		March 1964	March 1964	March 1964	Sep. 1967
Passing position of traffic loads		Quarter of span	-	-	Quarter of span
		Case #5	Case #6	Case #7	Case #8
Visible damage	Crack	Lengthwise and crosswise	Lengthwise and crosswise	Lengthwise and crosswise	Lengthwise and crosswise
	Splitting	-	-	Rising of surface	-
	Impurity	Free lime	Water leakage	-	-
Place of damage		Haunch part	Haunch part	Haunch part	Haunch part
Design code		Feb. 1980	March 1964	March 1964	March 1964
Passing position of traffic loads		Quarter of span	Quarter of span	Quarter of span	Quarter of span

Table 3. Inference Results obtained using Existing System

Causes / Cases	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47
case #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
case #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
case #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
case #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
case #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
case #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
case #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
case #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

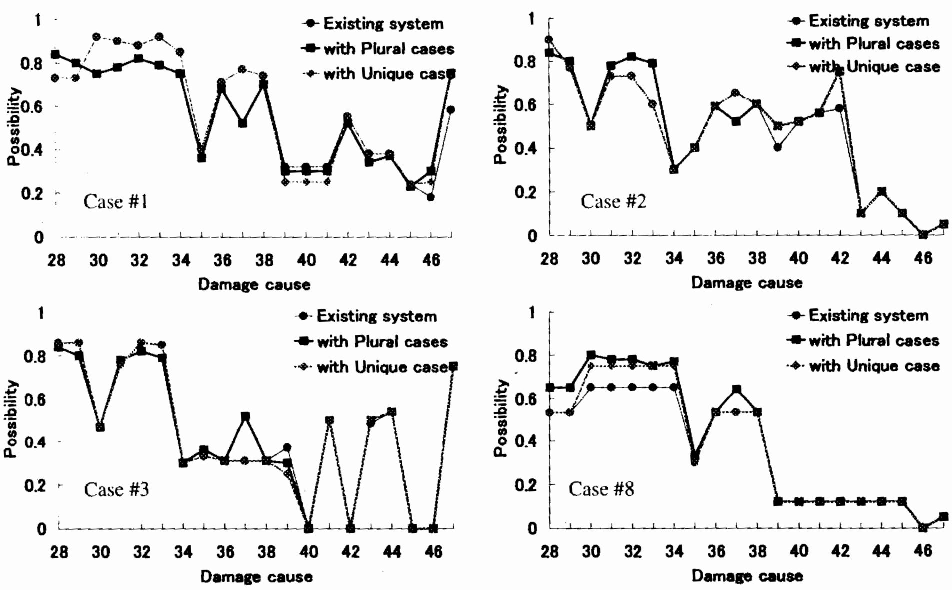

Fig.2 Possibilities of damage causes.

4. DAMAGE CAUSE INFERENCE AFTER THE RULE BASE REFINEMENT

Presenting the inference results of the existing system which are regarded as secured information by taking them up as training samples, the rule base was refined. After that, the damage cause was inferred using the refined rule base. However to prevent the training samples from being changed in the course of the refinement of the rule base, all the node training certainty degrees are determined to be "1.0," and all the rule certainty degrees are settled as "0.1." Furthermore the rule certainty degree after the rule base refinement is used without any rectification in inferring the damage cause, and the node value and node certainty degree are determined respectively to be "0.5" and "0.1" in consideration of the fact that the possibility of the damage cause is unknown information. The training samples are the inference results of the existing system listed in Tables 2 and 3.

It is examined how the inference results after the refinement of the rule base are subjected to the influence owing to the presented cases in the event that plural cases are simultaneously presented.

By presenting all the 8 cases simultaneously, refinement of the rule base is made. After that, the possibility of the damage cause complying with the individual cases is inferred. The inference results obtained in this manner are depicted in Fig. 2. In the figure, the inference results of the existing system and the results in the event that unique cases are presented are concurrently shown for the sake of comparison.

When the rule base is refined by simultaneously presenting all the cases standing on these results, it is noted that the ratio that coincides with the training samples was lowered owing the refinement by to the unique cases. This is because the inference accuracy for the individual cases is lowered owing to the fact that the rule base is refined for the purpose of being in agreement with all the training sample. However the rule base that is determined from the information obtained at a time should intrinsically be identified in a single piece, and the error is small despite the fact that just a single pair of the rule base is obtained with all the cases as the training samples. Thus it can be safely be said that the effect of the rule refinement is remarkable. This suggests that the inference system into which the inference performance of the existing system is incorporated can very easily be constructed.

5. CONCLUSIONS

In this study, construction is made with a versatile inference system attached with rule base refinement functions expressed by mutually-linked networks taking up the relations between the hypotheses as compositional elements. The inference system in question not only can perform usual inference by converting the knowledge of the expert system into a rule, but also can refine the rule base by using the inference results of the existing system for concrete cases as training samples.

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