Expert Systems for Assessment of Structural Damage

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KEYWORDS

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ABSTRACT

Several versions of an expert system called SPERIL have been developed since 1980. A brief review and introduction of these systems are presented herein. In this paper, a new version incorporating a learning procedure will be described. The learning procedure can be used to enable the computer system to (a) learn new knowledge, (b) verify knowledge base, and (c) modify knowledge base. In addition, fuzzy sets, certainty factors, and damage functons are used for the selection of suitable weighting factors in the decision-making process.

Systems à base de connaissances pour l'évaluation de dommage les structures

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MOTS-CLÉS

Niveau de dommage, Systèmes experts, Ensembles flous, Procédé d'apprentissage

SOMMAIRE

Plusieurs versions d'un système expert appelé SPERIL ont été développees depuis 1980. Ces systèmes sout présentés et revues brièvement daus ce papier. Une nouvelle version qui incorpore une procédure d'apprentissage est e'galement présentée. Eelte procedure peut permettre à l'ordinateur (a) d'apprendre de nouvelles connaissances, (b) de vérifier les connaissances existantes dans le système, et (c) de modifier ces connaissances. De plus, les ensembles flous, factors de certitude, et fonctions de dommages sont utilisés dans la selection de poids appropries an processus de prise de décision.

INTRODUCTION

Many problems in the real world are extremely complicated. For example, the behavior of existing structures under severe loading conditions is not clearly understood due to incomplete and insufficient information to-date. Complex decisions are usually made by experts on the basis of their intuition and judgement such as in the case of making damage assessment for existing structures. Although the damage assessment techniques exist in practice, the detailed methodology including in the decision-making process remains as priviledged information for a relatively few experts in the profession. Therefore, it is both important and timely to develop a rational and systematic decision-making process for the assessment of structural damage.

To-date, several expert systems have been developed for damage assessment.[1-5] The first two versions are called SPERIL-1 and 2. In SPERIL-1[1-5], an arbitrary damage measure ranging from zero ("no damage") through ten ("total collapse") is used. The extended theory of evidence[6] is used to integrate various evidences. In SPERIL-2[7-8], the integer exponent n of the order of failure probability 10^{-n} is used as a measure of structural safety. SPERIL consists of the following three parts a) inference machine b) knowledge base and c) memory. The inference machine contains several methods for the purpose of reasoning, and the solution is obtained on the basis of available data in the memory according to rules in the knowledge base. In the knowledge base, there are a) knowledge in terms of rules for damage assessment, and b) metarules with which the rule group and a suitable inference method may be chosen in SPERIL-2.

Recent investigations at Purdue University have led to the development of a practical expert system for damage assessment. A major difficulty in knowledge acquisition lies with effective communication between specialists of expert systems and domain experts. Usually a complex problem in an expert system is divided into a series of simple questions. In the computer program, several features are combined to determine global damage of the structure. In designing such a program, it is difficult to know a priori how much weight should be attached to each feature being used. Furthermore, some elements of the knowledge may be associated with great uncertainty or even be wrong. In such cases, a learning machine may be used to (a) automatically acquire new knowledge from domain experts, and (b) verify and modify knowledge base. It is desirable to incorporate a learning machine into a practical expert system. For this purpose, the SPERIL-3 is being developed on the bases of a preliminary version which was called CES-I. The system CES-I has been programmed and is currently accessible on the Unix CB machine of ECN at Purdue[9]. In this paper, a summary of CES-I is presented and the the development of the system SPERIL-3 is briefly described.

CONSTRUCTION OF CES-I

CES-I (originally called CES-BABY) is an expert system for damage assessment of existing structures which basically consists of the following four parts: inference machine, knowledge base, memory and learning machine. In regard to its "intelligence", this system is a crude beginning. However, this system is expected to grow continuously and may become a bonafide expert through its learning process.

In the memory, mainly two kinds of information are stored: namely information for current assessment and historical recod of assessments including such items as the name of structure, structural material, height or number of stories, areas of floors, shapes, soil condition and foundation, building usage, design parameters, presence of walls. Data collected from the inspection and testing of the structure, such as the size, number, and location of cracks, the time history of recorded ground motions and structural response in the form of accelerograms are stored as information for current assessment. Historical records consist of two parts: historical records for each structure and historical records for the work of the expert system machine. The former will be used as a file for each structure. The latter is designed specially for the purpose of learning.

The iterative procedure suggested by Yao, et. al.[10], is used as a heuristic procedure for making decisions. The questions to be asked are classified into different categories such as general information, inspection procedure, and loading condition. The order of these questions is ranked according to the degree of difficulties for obtaining information . At the beginning of asking each category of questions, the machine may ask the following question: "Could you give me some information on ` * * * ´ category of questions?" If the user answers YES, the machine will then ask this kind of questions. Otherwise, the machine will ask if the user can give any other information about the next category. Meanwhile, the machine put "* * *" category of questions in the tail end of the catalogue of questions. If the results are still not sufficient for determining the structural condition after having asked all categories of questions, the machine may suggest user to collect more information which is involved in unanswered categories of questions. In this manner the questions to be asked may become more reasonable through man-machine dialogue.

A normalized index method as proposed by Bresler and Hanson[11] is extended to both linguistic and numerical expressions for combining various evidences from different knowledge sources. In this method, the value of damageability index of each element (event) is normalized according to lower limit (damage threshold) and upper limit (ultimate damage). Meanwhile weighting factors are used to estimate the contribution of various elements (events).

In CES-I, the learning machine is used to mainly accomplish the following three tasks: (a) learn new knowledge, (b) verify knowledge base and (c) modify knowledge base.

During each practical application of damage assessment for a building, the machine may ask several questions for new phenomena of damage. If they are not already included in the knowledge base, the machine will put new knowledge into knowledge base. Although the new knowledge as written by the machine may be rather rough, they can be improved continuously through the learning process.

Through calibration between experts´ and machine´s assessments each term of knowledge in the knowledge base may be verified and modified. Two coefficients D_s and D_v are defined as degree of dispersity and degree of deviation respectively. The degree of dispersity D_s may be considered as a measure of the accuracy for the knowledge applied to ith knowledge source, and the degree of deviation D_v as a measure of the certainty factor for ith knowledge source.

Knowledge modification is included in two aspects in this study. One is the modification of wrong knowledge and the other is to change the weighting coefficients of corresponding knowledge sources. Those that appear to be good predictors of overall success (when both D_s and D_v are small) will have their weights increased. On the other hand, for the cases where D_s are found to be greater than some critical values, their weights will be decreased. Meanwhile, when the degrees of deviation D_v in certain parts of knowledge sources are found to be greater than critical values, the knowledge of corresponding parts should be modified accordingly.

In this way, the machine may be used to automatically add, delete and modify the knowledge base. With the use of this learning machine, it is possible for domain experts to build certain parts of the expert systems by themselves even if they are not specialists of expert systems. Meanwhile, the system may be improved continuously using the learning process.

FORMULATION OF SPERIL-3

Based on CES-I[9], the consultant process of SPIRIL-3 is designed in a hierarchical fashion. Following Bresler[12], two phases of consultants are used in SPIRIL-3 in order to obtain a good assessment of the structural damage and to keep the cost of the assessment low. In phase I, questions asked include general information, design quality, construction quality and feelings resulting from inspection. Based on each type of information, suggestions may be made such as "no action is needed", "laboratory tests are required", "loading tests is required". In phase II, more detailed information is to be requested and decision is

made according to information from both phases.

Knowledge in SPIRIL-3 is classified into several different categories. In regard to the knowledge representation in the development of SPIRIL, SPIRIL-1 is a rule-based system and the rules of SPERIL-1 are written in a format close to natural rule sentences. SPERIL-2 is basically a rule-based system. However, logic is used to represent the rules, facts and data from the existing structure. When we tried to build a learning machine, it is found that the frame-like structure[13-15] has more advantage in representing sequences of events and for knowledge acquisition and modification. Based on this observation, a frame structure is used to represent knowledge in CES-I. In rule-based systems, knowledge is represented as a IF-THEN rule, e.g.,"IF premise is satisfied, THEN action takes place.". In frame, knowledge is represented as a structured object. Frames, therefore, are usually called prototypes for they represent typical situations. A frame consists of a set of slots that specify the expected objects and events and each slot has own name and values. The slot value can be a constant, a variable or a function, which can be defined by using another frame. In this way, complex knowledge may be represented by using a series of frames.

From engineers´ viewpoint, a frame is like a table. One table may involve many pieces of knowledge that should be represented by many "IF-THEN " rules. One of the main advantages of frame representation is that the information is represented explicitly. Because each slot in a frame has its own name and values, which make explicit what we should expect to know. By checking each note corresponding to each slot value whether filled or empty, the available information can be obtained or the lost information will be demanded. In the frame structure, it is easy to add, delete and modify slots. The learning procedure can be implemented by adding, deleting and/or modifying slots and corresponding values of prototypes in knowledge base. The advantages and disadvantages of each method of representation, however, depend on the specific application and features of knowledge. In SPIRIL-3, a combination of rule-base and frame is used as representation methods of knowledge[16]. The rules are divided into several levels according to their roles in the decision-making process. Several overall control rules form the core of the knowledge base, and these control rules cannot be changed during the learning process.

Several combination methods are used and compared with one another to obtain reasonable conclusions. In addition, the normalized index method is used as a qualititive measure. Two other methods called weighted matrix method and extended Shafer method[17] are also used to provide more measures. In the former, the weight factor is used as a measures of degree of importance and belief of each element (event). In the latter, the certainty factor is used. Both statistical information and fuzzy information[18-23] can be incorporated herein.

The experience of using learning procedure in CES-I shows that, when we deal with qualitative problems, the weight of each event depends not only on the knowledge source but also on the degree of quality. In real-world problems, it is reasonable to consider continuous-valued logic. In general, it is clear that if the rule A -> B holds, it does not implies that the rule $\overline{A} \rightarrow \overline{B}$ also holds. As an example, the foundation failure is a good predictor on structural failure. Thus, a big weight may be assigned in structure damage assessment when the foundation appears to be damaged. On the other hand, we can not test whether the structure is damaged or not with no damage in the foundation. Consequently, it may get a very small weight on the assessment. As a result, different degrees of damage in the foundation may have different weight on the assessment of structural damage. Generally speaking, it is reasonable for the learning machine to use dynamical weighting functions rather than to use constant weighting factors. Based on this observation, a more reasonable and effective learning model with dynamical weighting functions is used in SPERIL-3.

Another feature of SPIRIL-3 is in its explanation facilities. The explanation machine does the following tasks: 1) explaining why a conclusion is given, 2) explaining the reason of asking for additional informations 3) ask experts' suggestions of explanation in order to modify its knowledge base. An attempt is made to use the same knowledge base in several ways. The system can be useful not only for the purpose of learning and explanation but also for teaching new engineers.

DISCUSSION AND CONCLUDING REMARKS

A brief review of the development of expert systems for damage assessment is described. There seems to be a bottleneck in knowledge acquisition for the development of a practical system, which is not only time-consuming but also difficult in communicating with experts. A learning machine can be developed for automatic knowledge acquisition. Meanwhile, domain experts may interact with the knowledge bases and teach computer system directly . Therefore, the system can be continually improved by learning important knowledge directly from both experts and its own "experience".

It must be recognized, however, that most current learning systems work in a fixed manner as developed by the designer. In fact, such systems learn automatically only parts of knowledge. Subjective knowledge and experience of an expert, however, imply a higher level of intellectual organization. The emphasis therefore on learning the overall organization of knowledge and acquiring control knowledge, knowledge about when and how to use certain facts, is very important. Meanwhile, it should be recognized that most complex decision is made in terms of experts' intuition and judgement. It is often difficult for domain expert

to describe knowledge in terms that are precise and complete, and contain sufficient information for use in a computer program[24]. Nevertheless, learning from incomplete or uncertain information can also be useful.

More effective knowledge representation methods are desirable[25] and should be developed for improving both the decision-making process and the learning method. More combination methods are also desirable for combining different types of evidences in various domains.

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