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THE USE OF EXPERT SYSTEMS IN SEISMIC RISK ANALYSIS

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ABSTRACT

Regional damage estimation is a necessary step in the seismic policy process, which is often hampered by a lack of information on the seismic resistiveness of buildings and other structures. This paper describes an expert system for determining the construction type of buildings, based on information obtainable from a visual inspection. The expert system is incorporated in a computer program for estimation of seismic damage to buildings. Several approaches are considered in the development of the expert system, including the use of special types of neural nets, and treatment of uncertainty using both Bayesian Probability models and Dempster-Shafer Calculus.

INTRODUCTION

Estimation of losses due to earthquake shaking and related hazards is a necessary step in the seismic policy process. The seismic vulnerability of a structure depends largely on its construction type. Consequently, accurate estimation of post earthquake damage to buildings relies on the correct determination of their construction types.

The use of expert systems to obtain and employ information interactively to determine the construction type and estimated damage to buildings, is a recent innovation in seismic damage estimation. The advantage in the use of expert systems is that fairly general information obtainable from a non-engineer can be used in combination with the expert system's knowledge base to make fairly complex assessments of the building's construction type and seismic vulnerability.

This paper discusses an expert system incorporated in a damage estimation program, and describes the various steps in its development. Different approaches were considered in this study, particularly the use of neurological tables (fuzzy cognitive maps), which are easier to construct than traditional rule-based expert systems.

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Handling uncertainty is of major concern in developing an expert system. In cases where there is more than one possible structure type, the likelihood of each type should be determined This paper explains how Bayesian probability can be used to determine the uncertainty in the results of the expert system and demonstrates that fuzzy cognitive maps can yield identical results to those obtained from the Bayesian probabilistic models. The use of Dempster-Shafer Calculus [1,2] to handle uncertainty in the expert system is also discussed

DEVISING THE EXPERT SYSTEM

In order to determine the construction type of a building, the expert system obtains information from the user through a series of general questions which can easily be answered based on a visual inspection of the building. The program also displays graphical images to assist the user in answering these questions as shown in Figure 1.

The program then employs the user's responses to determine the possible structure types, and the relative likelihood of each one

The expert system developed for this project consists of the following components

1) A graphical interface to facilitate user interaction, enabling the user to provide responses to the different questions presented by the expert system. This interface was developed using the Microsoft Windows programming environment.

2) An "inference engine", which uses the responses provided by the user in a reasoning chain to determine the different possible structure types.

Two approaches were considered in designing the inference engine The first was the classical rule-based approach in which knowledge is represented in the form of "if-then" rules, and responses provided by the user represent the known facts. The known facts are then propagated through the rules using the forward chaining mechanism to determine the possible structure types This approach worked well, however, it required substantial development time to design the inference engine, encode the rules, and test the whole system.

The second approach considered in designing the inference engine was to use "fuzzy cognitive maps". A fuzzy cognitive map is a neural network which can represent knowledge like any expert system. This method, first suggested by Kosko [3, 4], has some advantages over traditional rule-based systems, particularly in its ability to deal with multiple sources of knowledge even when they disagree. In addition, since components of the expert system such as the inference engine are already incorporated in the neural network, fuzzy cognitive maps result in considerable savings in development time over rule-based systems

This second approach employs a "Hopfield neural network", consisting of a series of nodes, each of which represents a particular concept or object that is relevant to the problem. Weighted, directed connections among the nodes represent the relative strengths of the causal relationships. A positive weight means the source node causes the destination node to increase in significance or become more powerful, a negative weight means the source causes the destination to decrease or become less powerful.

In the present implementation, the nodes of the fuzzy cognitive map represent one of two things - (1) possible structural types, or (2) physical/visual attributes of buildings. In all, there are 34 nodes in the map, comprised of 13 structure types (referred to as "hypotheses") and 21 physical attributes (referred to as "evidence") The 13 structure types are intended to represent an exhaustive list of possible structure types, and correspond to those enumerated in a previous study [5] Table 1 lists these possible structure types. The 21 evidences represent physical attributes of a building that may be determined by visual inspection, such as evidence of wood framing or brick masonry. Weights are assigned to indicate causal relationships between nodes As an example, the relationship between unreinforced masonry (URM) building (structure type) and evidence of masonry with header courses (physical attribute) might be represented by a weight of 0.6 (from the node representing the header courses to that representing the URM buildings), indicating that if a building is a URM, then there is a strong likelihood of brick header courses being visible. Evidences can also be connected together by weights so that the appearance of one evidence may increase or decrease the likelihood of other evidences. In our fuzzy cognitive map, weights linking evidences to all other evidences are zeros, as are weights linking structure types to one another. In the neural network implementation, the evidences lead to increased or decreased probabilities of the hypotheses, but there is no reverse influence of the hypotheses on the evidences. The non-zero weights in the map were obtained by eliciting the opinions of a panel of experts The probability of each structure type, given certain evidences, is obtained from the map as an output.

It has been established that a Hopfield network based on a neurological table that is symmetric and has zeros along the diagonal is guaranteed to stabilize The fuzzy cognitive map of the present implementation has zeros along the diagonal (causative relationship of structure types or evidences to themselves), but is not symmetric It is therefore not guaranteed to converge, however, it was found that our implementation does, in fact, converge.

HANDLING UNCERTAINTY IN EXPERT SYSTEMS

At the end of the user-query, the expert system arrives at a list of possible structure types Each type has a certain degree of probability associated with it, based on the user's responses. This section discusses how the probabilities are determined by the expert system, and will demonstrate that the probabilistic models used in the rule-based expert system and the fuzzy cognitive map can yield identical results. A procedure for handling the probabilities in the system using Dempster-Shafer Calculus [1,2] is also presented.

In the rule-based expert system, uncertainty is handled using a special form of the Bayesian updating rule, which we shall refer to as the logarithmic form of the Bayesian Updating Formula. A derivation of the logarithmic Bayesian Updating Formula follows.

The standard Bayes' Rule is:

$$P(H_i|e_j) = \frac{P(e_j|H_i)}{P(e_j)} \cdot P(H_i) \tag{1}$$

$P(H_i \mid e_j)$ is known as the posterior probability of H_i given e_j.

$P(H_i)$ is known as the prior probability of H_i.

Similarly,

$$P(\overline{H}_i|e_j) = \frac{P(e_j|\overline{H}_i)}{P(e_j)} \cdot P(\overline{H}_i) \tag{2}$$

Where $\overline{H}_i$ is the complement, or negation of H_i.

Dividing Equation 1 by Equation 2

$$\frac{P(H_i|e_j)}{P(\overline{H}_i|e_j)} = \frac{P(e_j|H_i)}{P(e_j|\overline{H}_i)} \cdot \frac{P(H_i)}{P(\overline{H}_i)}$$

which can be written as

$$O(H_i|e_j) = \lambda(e_j|H_i) \cdot O(H_i) \tag{3}$$

Where

$O(H_i|e_j)$ is the "posterior odds" of H_i given e_j and is equal to $\frac{P(H_i|e_j)}{P(\overline{H}_i|e_j)}$

$O(H_i)$ is the "prior odds" of H_i and is equal to $\frac{P(H_i)}{P(\overline{H}_i)}$

and $\lambda(e_j|H_i)$ is the "likelihood" of e_j given H_i and is equal to $\frac{P(e_j|H_i)}{P(e_j|\overline{H}_i)}$

In cases where there is more than one evidence $(e_j \ldots e_n)$, the posterior probability of H_i given $(e_j \ldots e_n)$ is:

$$P(H_i|e_j \ldots e_n) = \frac{P(H_i, e_j \ldots e_n)}{P(e_j \ldots e_n)} = \frac{P(e_j|H_i, e_{j+1} \ldots e_n) \cdot P(H_i, e_{j+1} \ldots e_n)}{P(e_j \ldots e_n)}$$

Assuming that all the evidences are conditionally independent.

$$P(H_i|e_j \ldots e_n) = \frac{P(e_j|H_i)P(e_{j+1}|H_i)\ldots P(e_n|H_i)P(H_i)}{P(e_j \ldots e_n)}$$

By following the same derivation used in the case of a single evidence, one can show that

$$O(H_i|e_j \ldots e_n) = \lambda(e_j|H_i).\lambda(e_{j+1}|H_i)\ldots\lambda(e_n|H_i).O(H_i) \qquad (4)$$

where O $(H_i \mid e_j \ldots e_n)$ is the posterior odds of H_i given the evidences $(e_j \ldots e_n)$.

Taking the logarithm of both sides of Equation 4

$$\ln O(H_i|e_j \ldots e_n) = \ln(\lambda(e_j|H_i)) + \ln(\lambda(e_{j+1}|H_i)) + \ldots + \ln(\lambda(e_n|H_i)) + \ln(O(H_i)) \qquad (5)$$

Since λ $(e_j \mid H_i)$, $O(H_i)$ takes values in the range $[0, \infty]$, ln $(\lambda(e_j \mid H_i))$ and ln $(O(H_i))$ will take values in the range $[-\infty, \infty]$

If evidence e_j and the hypothesis H_i are independent, then

$$\ln(\lambda(e_j|H_i)) = \ln\left(\frac{P(e_j|H_i)}{P(e_j|\overline{H_i})}\right) = \ln\left(\frac{P(e_j)}{P(e_j)}\right) = 0$$

This means that ln $(\lambda(e_j \mid H_i))$ is positive if e_j support H_i, negative if e_j negates or contradicts H_i, and zero if e_j has no effect on H_i (e_j and H_i are independent). Once the logarithmic values of the posterior odds are calculated, the posterior probabilities can be derived from them as follows.

$$\ln(O(H_i|e_j \ldots e_n)) = \sum_{k=j}^{n} \ln(\lambda(e_k|H_i)) + \ln(O(H_i))$$

Call the above quantity *sum*, i.e , $sum = \sum_{k=j}^{n} \ln(\lambda(e_k|H_i)) + \ln(O(H_i))$

$$O(H_i|e_j \ldots e_n) = e^{sum}$$

$$\frac{P(H_i|e_j \ldots e_n)}{1 - P(H_i|e_j \ldots e_n)} = e^{sum}$$

$$P(H_i|e_j \ldots e_n) = \frac{e^{sum}}{1 + e^{sum}} = \frac{1}{1 + e^{-sum}} = sigmoid(sum) \qquad (6)$$

where

$$sigmoid(x) = \frac{1}{1 + e^{-x}}$$

This demonstrates that the Hopfield net can result in the same probabilities given by Bayes' rule if:

1. The evidences are connected to the hypotheses by weighted links and each link has a weight equal to ln $(\lambda(e_j \mid H_i))$

2. Each node which represents a hypothesis has a bias term equal to ln $(O(H_i))$

3. All nodes which represent hypotheses have a sigmoid activation function.

This probabilistic model was implemented in both expert system approaches discussed earlier and has resulted in satisfactory performance

The prior odds are calculated assuming equal probabilities to each of 13 possible structure types Therefore

$$P(H_i) = \frac{1}{13}, \quad O(H_i) = \frac{\frac{1}{13}}{1 - \frac{1}{13}} = \frac{1}{12}$$

The values of ln $(\lambda(e_j \mid H_i))$ were obtained directly by consulting a panel of experts on how strongly each structural type supported the presence or absence of the different evidences The experts were asked to give a value between -1 and +1 for each value of ln $(\lambda(e_j \mid H_i))$

Using Dempster-Shafer Calculus to Handle Uncertainty in the Expert System

Another approach for dealing with uncertainty in the expert system using Dempster-Shafer Calculus (belief functions) [1,2] was investigated during the course of this project Dempster-Shafer Calculus is a method for determining probability ranges in cases where the available information is partial or incomplete. Unlike the usual probabilistic models which give a single value, the Dempster-Shafer approach gives a range which bounds the probability The advantage of using Dempster-Shafer Calculus is its ability to model ignorance. The user might not know the answer to some of the questions presented by the expert system. This is modeled in the Dempster-Shafer approach by widening the probability range depending on the level of ignorance.

According to the Dempster-Shafer terminology, the set of all possible structure types Θ is called the "frame of discernment"

The set of all possible subsets of the frame of discernment is usually referred to as 2^{Θ}, since it consists of $2^{(\text{number of elements in } \Theta)}$ different elements (2^{13} in our case).

A basic probability assignment, *m*, is associated with each element in the set of all possible subsets The bounds on the probability of any subset *A* of Θ are given by

$$Bel(A) \le P(A) \le Pl(A)$$

Where *Bel (A)* is the belief of *A*

$$Bel(A) = \sum_{B \subseteq A} m(B) \tag{7}$$

and *Pl (A)* is the plausability of *A*

$$Pl(A) = \sum_{B \cap A \neq \phi} m(B) \quad \text{(Note that } \phi \text{ is the Null set)} \tag{8}$$

In our prototype implementation we have used conditional Bayesian probabilities to define the basic probability assignments as described by Yen [2].

The likelihood values obtained previously were converted to conditional probabilities as follows:

$$P(H_i|e_j) = \frac{\lambda(e_j|H_i)O(H_i)}{1 + \lambda(e_j|H_i)O(H_i)} \tag{9}$$

The values of $P(H_i \mid e_j)$ were then considered as basic probability assignments. Yen [2] showed that the basic probability assignments obtained from the conditional probabilities could not be combined directly using Dempster combination rules. He suggests converting the basic probability assignments, *m*, into basic certainty assignments, *c*, performing the combination on the basic certainty assignments, and then converting the results back to basic probability assignments.

The following equation converts the basic probability assignments, *m*, to basic certainty assignments, *c*

$$c(A) = \frac{\frac{m(A)}{P(A)}}{\sum \frac{m(A)}{P(A)}} \tag{10}$$

To convert the basic certainty assignments, *c*, back to basic probability assignments, *m*

$$m(A) = \frac{c(A) \cdot P(A)}{\sum c(A) \cdot P(A)} \tag{11}$$

The following example demonstrates how Dempster-Shafer Calculus can be used to handle uncertainty in the expert system.

Example

Suppose that the possible structure types (H_i) are:

- Wood-frame buildings (W)
- Light metal structures (LM)
- Tilt-up structures (TU)

Assume that the prior probability for these structure types, based on available statistical information is P(W) = .5, P(LM) = .2, P(TU) = .3, from which one finds that the prior odds are: O(W) = 5/(1-.5) = 1.0, O(LM) = .2/(1-.2) = 25, O(TU) = 3/(1- 3) = .428

Suppose that the evidences (e_j) are:

- Presence of any wood siding (WS)
- Presence of any exposed wood framing (WF)
- Presence of metal or asbestos transite siding (MAS)
- Whether the height of the roof is more than or equal to 20 ft (H ≥ 20')

Suppose also that the logarithm of the likelihoods obtained from the panel of experts was

	W	LM	TU
WS	1.00	-1.0	-.35
WF	.10	-1 0	.60
MAS	-.35	1 0	-1.00
H≥20	50	- 1	.50

(These numbers correspond to the $\ln(\lambda(e_j|H_i))$ terms discussed previously)

During the inspection of the building only the evidences of wood siding (WS) and exposed wood framing (WF) were identified.

Using the Bayesian Approach

The evidence obtained from the inspection is used to modify the prior probabilities (according to the Logarithmic Bayes' Theorem) as follows.

Using Equation 5

ln(O(W | WS,WF)) = 1 0 + 0.1 + ln(1) = 1 1
ln(O(LM | WS,WF)) = - 1.0 - 1.0 + ln(25) = - 3.386
ln(O(TU | WS,WF)) = - 0 35 + 0 6 + ln(428) = - 0.5973

From which the following probabilities are obtained using Equation 6

P(W | WS, WF) = 75, P(LM | WS, WF) = 033, P(TU | WS, WF) = 355

After normalizing

P(W | WS, WF) = 66, P(LM | WS, WF) = .03, P(TU | WS, WF) = .31

Using Dempster-Shafer Theorem

According to Dempster-Shafer the likelihood table has to be converted to probabilities $P(H_j \mid e_i)$ (This step is done by using Equation 9 and normalizing the calculated probabilities)

	W	LM	TU
WS	.698	080	.222
WF	.501	080	419
MAS	.433	424	143
H≥20	.387	.189	424

The above probabilities could be assumed equal to the basic probability assignments. The basic certainty assignments for the first two evidences, using Equation 10, are:

	W	LM	TU
WS	.55	.1577	.2918
WF	.3581	1429	.4990

Combining the above basic certainty assignments using the Dempster combination rule one gets

$c(\text{W}) = .5395$ $\qquad$ $c(\text{LM}) = 0617$ $\qquad$ $c(\text{TU}) = 3988$

Converting the basic certainty assignments to basic probability assignments using Equation 11, one gets

$m(\text{W}) = .67$ $\qquad$ $m(\text{LM}) = 03$ $\qquad$ $m(\text{TU}) = 0.3$

These results are almost identical to those obtained from Bayes' Theorem. The flexibility of Dempster-Shafer Calculus is more appreciated if we reformulated this example as follows·

Assume the evidence of wood siding (WS) gives a probability of 698 for wood structure(W), and we don't know how this evidence affects either the tilt-up (TU) or the light metal (LM) structures

$m(\text{W} \mid \text{WS}) = 698$ $\qquad$ $m(\text{TU or LM} \mid \text{WS}) = .302$

Similarly assume that the appearance of exposed wood framing (WF) reduces the probability of light metal (LM) to .08, and we don't know how the remaining probability is distributed between tilt-up (TU) and wood-frame (WF) structures.

$m(\text{W or TU} \mid \text{WF}) = 92$ $\qquad$ $m(\text{LM} \mid \text{WF}) = 08$

If WS is observed

$m(\text{W} \mid \text{WS}) = 698$ $\qquad$ $m(\text{TU or LM} \mid \text{WS}) = 302$

Using Equations 7 and 8

Bel (W) = .698	*Pl* (W) = .698
Bel (TU) = 0	*Pl* (TU) = .302
Bel (LM) = 0	*Pl* (LM) = .302

This means that the probability of wood is .698 and the probability of either TU or LM is between 0 and .302. Assuming that both (WS) and (WF) are observed, one can find the combined basic probability assignments as follows.

- Convert basic probability assignments to basic certainty assignments using Equation 10

$c(\text{W} \mid \text{WS}) = .698$ $\quad$ $c(\text{TU or LM} \mid \text{WS}) = .302$

$c(\text{W or TU} \mid \text{WF}) = .742$ $\quad$ $c(\text{LM} \mid \text{WF}) = .258$

- Apply the Dempster combination rule

	c(W)=.698	c(TU or LM)= 302
c(W or TU) = .742	c(W)=.518	c(TU)=.224
c(LM)=.258	$c(\phi)$=.18	c(LM)=.0779

Upon normalizing

$c(\text{W}) = .6318, \quad c(\text{LM}) = .095, \quad c(\text{TU}) = .2731$

- Convert the basic certainty assignments to basic probability assignments using Equation 11

$m\,(\text{W}) = 758, \quad m\,(\text{LM}) = .045, \quad m\,(\text{TU}) = 196$

The advantage of the Dempster-Shafer model over the Bayesian approach is the representation of ignorance. In the Dempster-Shafer approach the belief directly committed to a set of hypotheses is not distributed among its constituents until further evidence is gathered However, in the Bayesian approach the amount of belief committed to a hypothesis group is always distributed among its constituents.

CONCLUSIONS

1. Both rule-based systems and neural network approaches can be used successfully to design an expert systems for determining the construction type of buildings.

2. Using Hopfield nets (fuzzy cognitive maps) to devise expert systems is very efficient since most of the components needed for the expert system are already included in the neural net.

3. Using Hopfield nets with sigmoid activation functions and appropriate weights provides probabilistic values identical to those obtained using Bayesian Probability Theory.

4 Dempster-Shafer Calculus can be a powerful tool to handle uncertainty in the expert system, since it is more adept at modeling ignorance than the traditional probabilistic models

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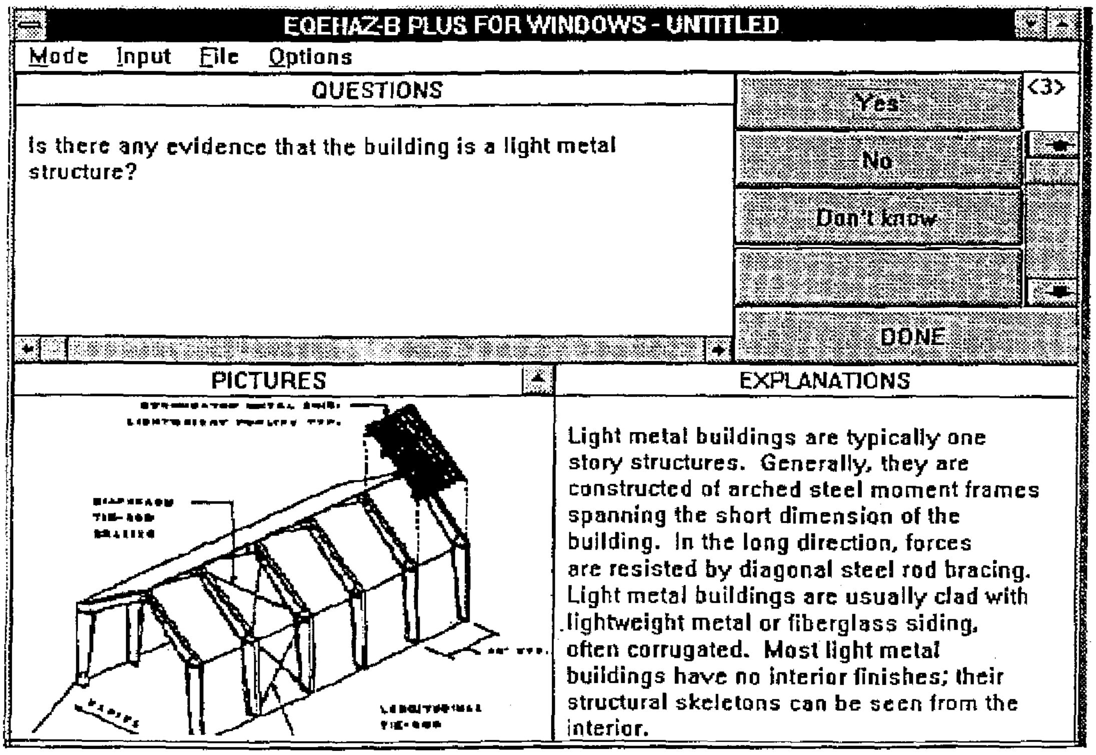

Figure 1. An example screen depicting the query process in the expert system

TABLE 1. Building Identifiers (after Reference [5])

Building Identifier	General Description
W	Wood buildings of all types
S1	Steel moment-resisting frames
S2	Braced steel frames
S3	Light metal buildings
S4	Steel frames with cast-in-place concrete shear walls
C1	Concrete moment-resisting frames
C2	Concrete shear wall buildings
C3	Concrete buildings with unreinforced masonry infill walls
S5	Steel-frame buildings with unreinforced masonry infill walls
PC1	Tilt-up buildings
PC2	Precast concrete-frame buildings
RM	Reinforced masonry
URM	Unreinforced masonry