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A hybrid approach of knowledge-based reasoning for structural assessment

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Abstract
A hybrid reasoning system is developed for damage assessment of structures. The system combines the use of a model of the structure with a knowledge-based reasoning scheme to evaluate if damage is present, its severity (severity and dimension) and its location. Using a given model (or several models), the structural dynamic responses to given excitations are simulated in the presence of different forms of damage. In a 'learning mode' an initial casebase is created with the principal features of these damage responses. When the system is working in its operating mode, data acquired by sensors are used to perform a diagnosis by analogy with the cases stored in the casebase, reusing and adapting old situations. Whenever a new situation is detected, it is retained in the casebase to update the available information. This paper describes the methodology and how the system is built and tuned to be ready for operation. This is illustrated by a numerical example of a cantilever truss structure and tested numerically and experimentally with a beam structure. Conclusions are presented with the emphasis on the advantages of using knowledge-based systems for structural assessment.

(Some figures in this article are in colour only in the electronic version)

1. Introduction

The need to apply global damage identification methods in complex structures has encouraged researchers to inspect changes in the vibration characteristics of structures. An excitation signal is applied and the resulting dynamic response is examined. Doebling *et al* [4] present a comprehensive literature review of damage identification and health monitoring methods based on vibration measurements for structural and mechanical systems. The basic premise of vibration-based damage detection is that the damage will alter the stiffness, mass or energy dissipation properties of a system, which, in turn, will alter the measured dynamic response of the system. Most of the methods developed to solve the damage identification problem regard it as a problem of identification, optimization, pattern recognition or classification.

The methodology proposed in this paper is based on a pattern recognition approach for structural assessment. The use of knowledge-based approaches to damage identification was suggested by Natke and Yao in 1993 [12]. However, the authors know of no references to using these approaches specifically for damage detection. On the other hand, in the field of structural design, some researchers [5, 8, 10] have applied case-based reasoning to bridge design. Because many modelling possibilities exist to explain the behaviour of structures, Raphael and Smith [14, 16, 15] describe an approach for selecting appropriate causal models for engineering diagnosis. They combine compositional modelling with model reuse to improving the quality of

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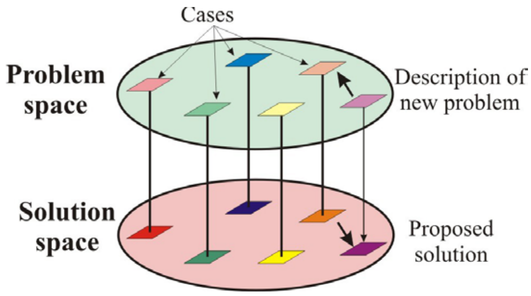

Figure 1. CBR system.

diagnosis. Model composition permits reasoning with multiple models containing explicit assumptions. Difficulties related to intractability during model composition are reduced by model reuse.

The systems in which an 'expert' applies his/her experience and knowledge to a situation can frequently provide the solution to a problem without resorting to an intensive investigation [18]. To solve the damage identification problem the wavelet transform (WT) is used to extract the principal features of a signal, case-based reasoning (CBR) is applied to obtain an initial diagnostic by analogy, and a self-organizing map (SOM) is trained as a classification tool to organize the old cases in memory, for the purpose of speeding up the reasoning process. Finally, when similar old cases are retrieved the damage severity and location are obtained directly from heuristics.

The basic definitions of case-based reasoning are presented in section 2. The methodology for damage identification is described in detail in section 3, which describes the extraction of the principal features from the structural response, organization of the existing knowledge, retrieval and adaptation of the solution to identify the damage. A case study is presented in section 4, in which a model and a real structure were used to test this methodology. Finally, conclusions are presented emphasizing the advantages of using knowledge-based reasoning for structural assessment.

2. Case-based reasoning (CBR)

2.1. *Introduction*

Humans are robust problem solvers; they solve difficult problems despite incomplete and uncertain knowledge, and their problem-solving competence improves with experience. All of these qualities are desirable for intelligent computer systems operating in the real world. Essentially, case-based reasoning (CBR) is a model of human reasoning. The idea behind CBR is that people rely on previous experiences when they need to solve problems, reusing solutions without thinking too much about the situation. It is based on the perception that new problems are often similar to previously encountered problems and, therefore, those past solutions can be used in the current situation [17]. There are many examples to illustrate this idea. In any field, when tackling a problem, a professional with many years of experience is generally considered to be more suitable than a recent graduate with brilliant grades. Doctors use diagnoses and treatments that were effective for

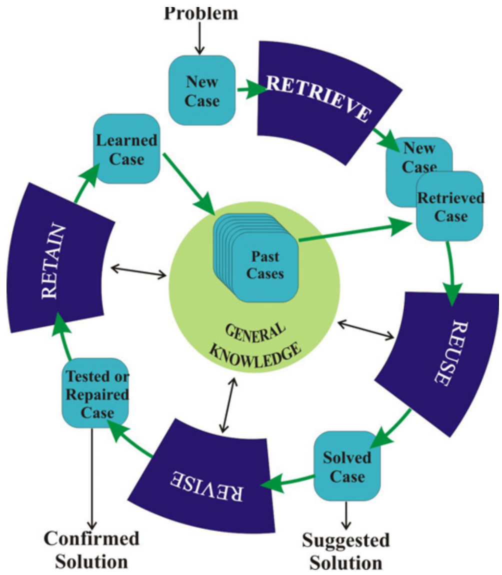

Figure 2. CBR cycle.

former patients when a new patient with similar symptoms appears. Lawyers frequently rely on reasoning based on proceedings or jurisprudence in the absence of well-defined concepts and precise laws. Chess players normally use automatic sequences of moves, which respond to variations of classic plays applied effectively to a set of similar situations. Daily life continually presents opportunities to apply case-based reasoning.

2.2. *Case representation*

A CBR system requires a set of experiences, 'cases', which are stored in a 'casebase'. A case is 'a contextualized piece of knowledge representing an experience that teaches a lesson fundamental to achieving the goals of the reasoner' [7, 9]. Each case is generally a register comprising a description (minimal representation) of a problem and the functional solution (see figure 1).

2.3. *CBR cycle*

To reach the goal, CBR methodology proposes a cycle of the four Rs (see figure 2). The CBR cycle basically consists of *Retain* cases for further *Reuse*. The aim is to *Reuse* these cases for solving new problems by analogy. A problem is solved by *Retrieving* a similar problematic situation (case or cases) from the past and *Reusing* its solution in the new situation. *Reusing* implies a procedure of adapting the *Retrieved* solution, which is then completed with the *Revision* [1]. In practice, it is difficult to distinguish between *Reuse* and *Revise* stages, and it may be best to think of these as a single *Adaptation* stage [3].

Case Retrieval is the first stage in the functional cycle of a CBR system. Given the description of a situation, or problem, and a set of objectives, or tasks, that have to be performed, it is a question of finding a similar case, or a small set of similar cases, that may be useful. In case-based problem solving, old situations are used as inspiration for solving new problems, because new situations rarely exactly match the old situations. However, old solutions must be modified to fit new situations. In this step, called *Adaptation*, there are two phases [7]: (1) *Determining* the differences between the case being considered and that retrieved from memory, and (2) *Modifying* the solution proposed in the retrieved case to take into account such differences. This modification is necessary to either adapt the previous situation to the new situation or repair it if it is not entirely correct. When the solution generated in the adaptation phase is not correct, the CBR system learns from the errors made. The *Revision* phase consists of two tasks: (1) *Evaluation* of the generated solution, and (2) *Learning* from the success and retaining the case if the solution is shown to be correct, or if not, correcting the system by resorting to possible methods of adaptation. Evaluating a solution is to judge the suitability of the proposed solution. Sometimes evaluation is performed in the context of previous cases; sometimes it is based on feedback from the real world; sometimes, it is based on simulation. Evaluation includes explaining the differences, justifying the differences, projecting the outcomes, and comparing and ranking alternative possibilities. At the moment of *Retaining* new cases into the casebase, the system must decide which information is to be retained and how it is to be incorporated into the memory structure. The learning process produces a modification of the structure as well as of the data of the casebase. Avoiding repetition of future failures is one of the learning benefits of a CBR system.

The form in which the cases are represented, how the similarity is determined, how the adaptation is done, and how the decision is made about the information necessary to be stored to obtain sufficient coverage of the application domain are topics that are mutually inclusive. For example, the better the capacity for adaptation the system has, the fewer cases it requires. Tools and methodologies used to tackle these subjects are described below. In many different areas attention is also being devoted to the combination of CBR with other methods. These combinations can involve CBR systems using other methods for support, CBR systems integrated with other methods, or CBR systems in a purely support role. Artificial neural networks (ANNs) are usually used for learning and generalization on knowledge and patterns. Case retrieval is essentially a pattern matching problem (a current input pattern or case with one or more stored patterns or cases). This is because ANNs, which are very efficient for matching patterns, are very useful tools for retrieving cases in CBR systems [11].

3. CBR methodology for damage identification

3.1. Overview

Recognizing the presence of structural damage can be a simple task performed on the basis of anomalies in the dynamic response. However, determining more precise information as to the position and nature of the damage is more complicated. This section describes a methodology for structural assessment (identification of the damage, its location, size and severity) using knowledge-based reasoning. First, in a 'learning mode' a model of the structure is used to simulate damage responses and to generate a set of cases. Using self-organizing maps (SOMs) as a classification tool [6], an initial casebase is built. This casebase is to be used in diagnosing future situations by

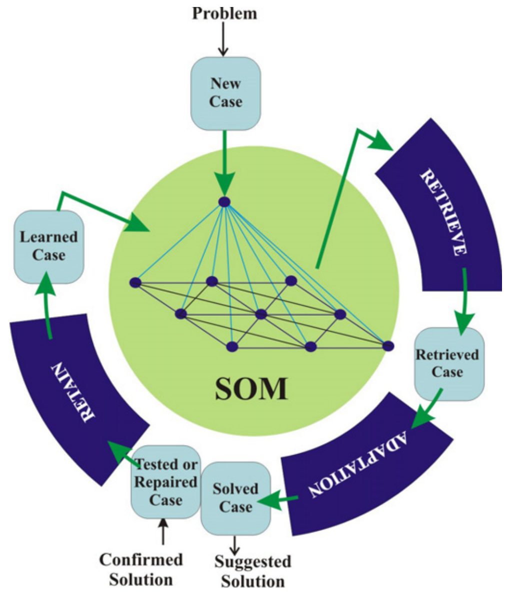

Figure 3. Proposed CBR cycle.

analogy (see figure 3). To reduce the number of input signals to the self-organizing map, without reducing the classification accuracy required, the wavelet transform is used to extract features from the measured signal while retaining most of the intrinsic information. When the system is in the 'operation' mode each new experience is retained once the damage has been detected.

This methodology is described using a numerical example of a cantilever truss structure with eight sections (see figure 4). The material and geometric specifications have been previously assigned. Two antiphase sine excitation forces are applied to elements 36 and 38. The element 1 was chosen as the sensor receiving the propagated wave. Briefly, the steps for the damage assessment are as follows.

Learning mode

(a) Choose the structure to study.
(b) Define what damage is to be identified (size and severity).
(c) Choose a set of cases which contain previous simulations of several structural damage cases.
(d) Build the casebase from the selected cases.

Operating mode

(a) Load the waveform detected by the sensor during the test of the selected structure.
(b) Retrieve the most similar cases from the casebase.
(c) Adapt the previous solutions to propose a new solution.
(d) Generate the outcome report and display the damage of the structure.
(e) Retain the new solution as a part of a new case once it has been confirmed or validated.

3.2. Cases

Before generating the cases, it is necessary to define which defects are the most representative, bearing in mind the damage to be identified. In other words, which are the most frequent

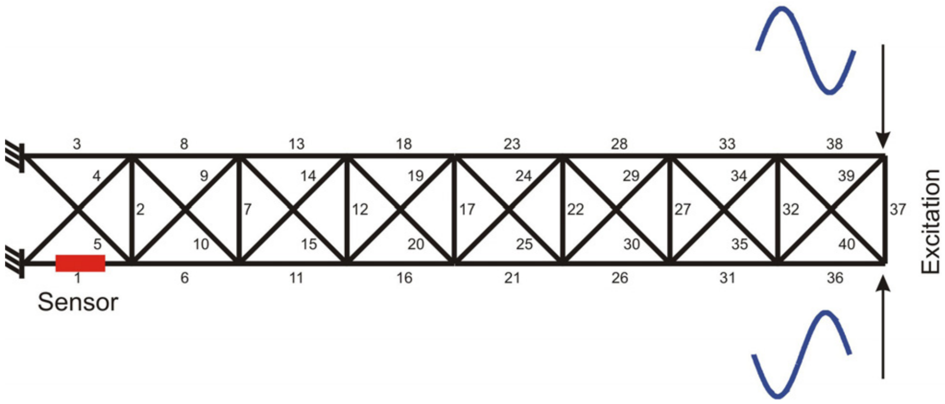

Figure 4. Cantilever truss structure.

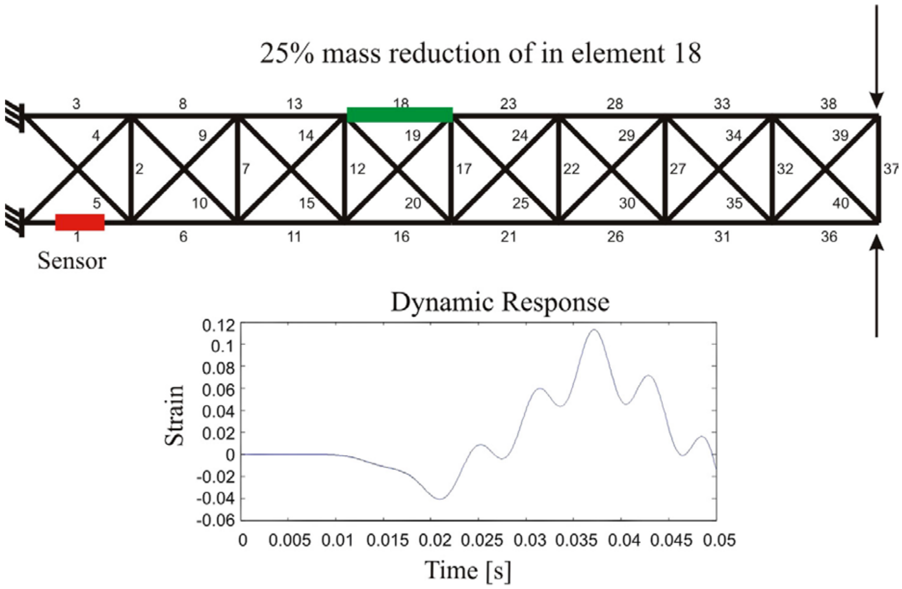

Figure 5. One case example: defect in element 18 and the corresponding dynamic response.

defects, which are the most important defects, which defects are really coherent, and which are the smallest and the biggest defects (severity and size). The casebase must not be loaded with damages that will never occur.

Each case is obtained by means of a model or several models of the structure, simulating the dynamic response to a given excitation in the presence of one or several defects. Each case is a data structure, which contains the defect of the structure (localization, severity, size, etc) and the simulated dynamic response. For example, figure 5 shows one case in which element 18 is subject to damage with a mass reduction of 25% and its dynamic response.

In this structure, we intend to identify defects for a variety of damage scenarios.

(a) No damage.
(b) Damage in a single element.
(c) Damage in two consecutive horizontal elements.
(d) Damage in three consecutive horizontal elements.
(e) Damage in four consecutive horizontal elements.
(f) Damage in five consecutive horizontal elements.
(g) Damage in two elements of the same section.
(h) Damage in three elements of the same section.
(i) Damage in four elements of the same section.
(j) Damage in five elements of the same section.
(k) Damage in all the elements of the structure.

This damage is a mass reduction of between 5% and 60%. A total number of 23 593 simulations were performed to obtain the dynamic responses for all possible cases in the above scenarios.

3.3. *Casebase building*

The casebase is an array in memory organizing all the cases to facilitate the search for the case most similar to the current problem. In the proposed methodology, the casebase is a self-organizing map. Each case is defined by the defect of the structure and the minimal representation of its damaged dynamic response. In this case, the minimal representation is the set of principal features that are extracted from the

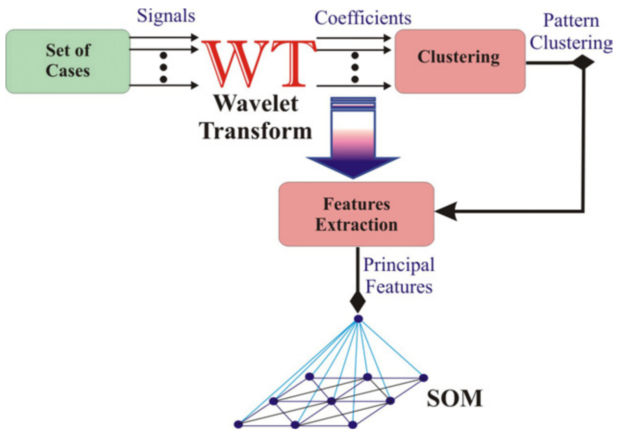

Figure 6. Casebase building.

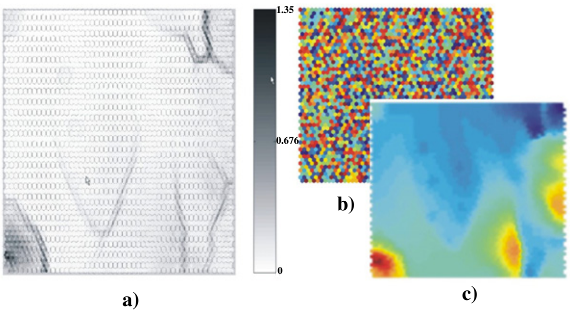

Figure 7. (a) U-matrix of the SOM. (b) Disorganized variables before learning. (c) Organized variables after learning.

coefficients of the wavelet transform applied to the dynamic response [2]. Figure 6 shows the process of feature extraction and building the casebase.

3.3.1. Feature extraction method. These principal features are extracted from the coefficients of the wavelet transform applied to the dynamic response. The wavelet coefficients are computed for each selected case. The coefficients at the same position in different cases are considered as samples of independent random variables. Therefore, bearing in mind the central limit theorem, each variable is approximately normally distributed. The maximal normal numbers and the maximal wavelet coefficients occur at the same positions, which determine the midpoints of the clusters. This pattern of clusters contains relevant signal information. Later, each feature is determined as the square root of the energy of the wavelet coefficients in the corresponding cluster [13]. This set of cases (defect of the structure and principal features of the signal) is used to build the casebase.

3.3.2. Self-organizing map training. After the set of cases is generated (defect and the principal features of the dynamic response) they are organized in memory for recovery at the required time, and an SOM is created and trained. This SOM has l neurons (one for each feature) in the input layer and $m * n$ clusters or neurons in the output layer. In the example, the SOM has 65 input neurons and $50 * 50$ output neurons. In each cluster, this network organizes the cases with similar characteristics. The unified distance matrix of an SOM (U-matrix) is shown in figure 7(a). These values indicate the distances between the weights of each neuron and its neighbourhood. High values indicate small correlation between clusters. The distribution of a variable into the SOM before training is shown in figure 7(b) and the organization of variables into the SOM after training is shown in figure 7(c).

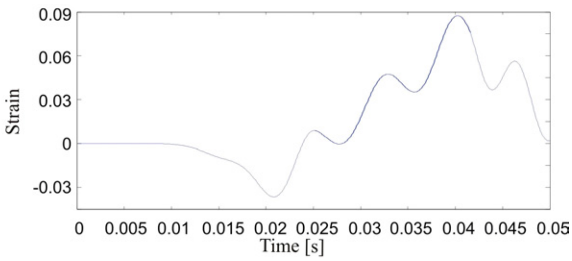

Figure 8. Signal detected by the sensor.

Table 1. Retrieved cases.

Damaged element	Severity	Distance
-15-	-30%-	0.003 62
-14-15	-10%-10%-	0.007 47
-11-14-15-	-10%-10%-10%-	0.011 23
-11-15-	-10%-10%-	0.014 83
-11-14-	-15%-15%-	0.015 17
-30-	-30%-	0.030 71
-29-30-	-25%-25%-	0.033 08
-29-30-	-30%-30%-	0.033 08
-14-15-	-25%-25%-	0.033 97
-25-	-30%-	0.035 30
-29-30-	-20%-20%-	0.040 81
-26-29-	-15%-15%-	0.041 04
-26-30-	-15%-15%-	0.041 62
-11-14-	-10%-10%-	0.042 53
-30-	-20%-	0.044 99

3.4. Retrieving

Checking the methodology or putting the system in operation mode can be performed by simulation, laboratory testing, and even in normal working conditions for real structures. Consider an example of the structure in operational mode and the signal shown in figure 8, which represents the dynamic response captured by the sensors. From this signal, the principal features are extracted using the clustering pattern previously defined (see figure 9). From these features the SOM retrieves a set of stored cases with similar characteristics. The activated clusters are shown in figure 10: the size of the black hexagon is proportional to the value of the data histogram (inversely proportional to the distance) in the corresponding cluster. This value indicates the distance between the input vector (principal features) and each cluster; in other words, it represents the similarity between the new case and the stored cases. The smaller the distance, the more similar the cases. Each black cluster corresponds to the best match, and white clusters correspond to the worst. Table 1 gives the cases (damaged element and its severity) stored in the activated clusters with their distances.

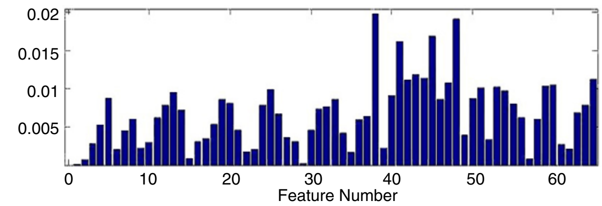

Figure 9. Principal features of the signal.

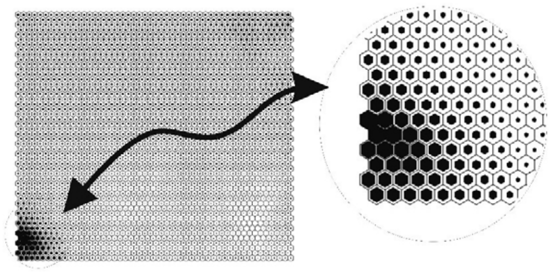

Figure 10. Activated clusters.

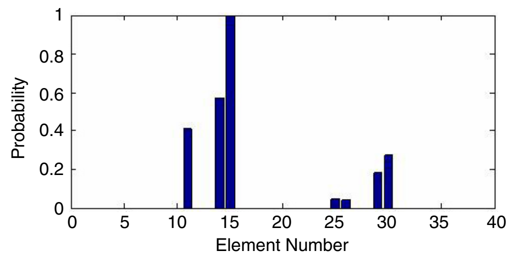

Figure 11. Proposed solution.

Table 2. Material of the beam.

Material	Young's modulus (GPa)	Density (kg m^{-3})
Aluminium	65.78	2710
Steel fixing	207	7680
Truss rod (piezo actuator)	0.28	7117

3.5. *Adapting*

From the retrieved cases (table 1), it is noted that the element 15 appears in the first four cases and the element 11 appears three times but not with the least distances. We want to reward (1) elements that are repeated several times—the more frequent the repetition, the higher the probability of being the 'winner'; and (2) similar cases—the smaller the distance, the higher the probability of being the 'winner'. To do this, a factor is calculated for the element, which is the sum of the inverses of the distances in which this element is present. For example, the factor for element 15 is

$$F_{15} = \frac{1}{0.003\,62} + \frac{1}{0.007\,47} + \frac{1}{0.011\,23} + \frac{1}{0.014\,83} + \frac{1}{0.033\,97} = 596.0277. \tag{1}$$

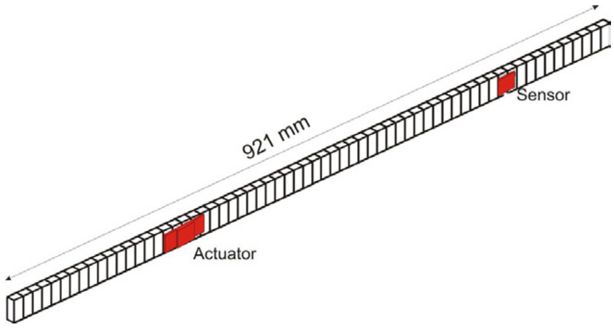

Figure 12. Beam model.

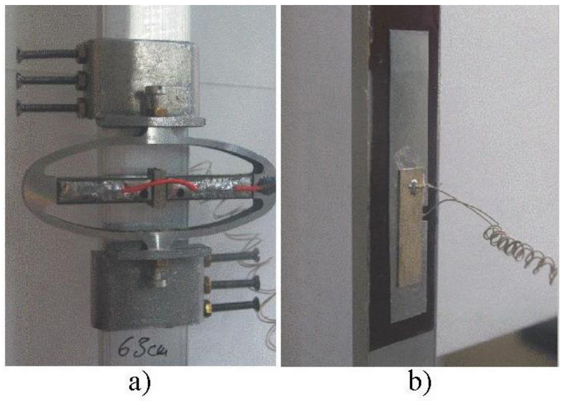

Figure 13. (a) Actuator. (b) Sensor.

Then, normalizing these factors, the probabilities of the damage in each element are calculated. The solution proposed to localize the defect in the example is shown in figure 11.

To calculate the size and the severity of the defects, a weighted average is computed, using as a weighting coefficients the inverse of the distances (see equations (2), (3)), where n is the total number of retrieved cases, and dim, dam and d are the dimension, the damage and the distance of each retrieved case, respectively. Note that $d(1)$ is the minimum distance. In this case the dimension is 1.7, which is rounded to two elements with a mass reduction of 29.86%.

$$\text{Dimension} = \sum_{j=1}^{n} \dim(j) * \frac{d(1)/d(j)}{\sum_{i=1}^{n} d(1)/d(i)} \tag{2}$$

$$\text{Severity} = \sum_{j=1}^{n} \text{dam}(j) * \frac{d(1)/d(j)}{\sum_{i=1}^{n} d(1)/d(i)}. \tag{3}$$

4. Beam case study

We applied the proposed methodology to damage detection in an experimental beam. Its physical characteristics are shown in figure 12 and table 2. It is equipped with a piezoelectric actuator (see figure 13(a)) that induces ending mode due to a sine wave excitation signal of 142.8572 Hz frequency and only one period duration. A sensor (see figure 13(b)) measures the bending strains (curvature) at the specified location. A finite element model is considered, as illustrated in figure 12, with a

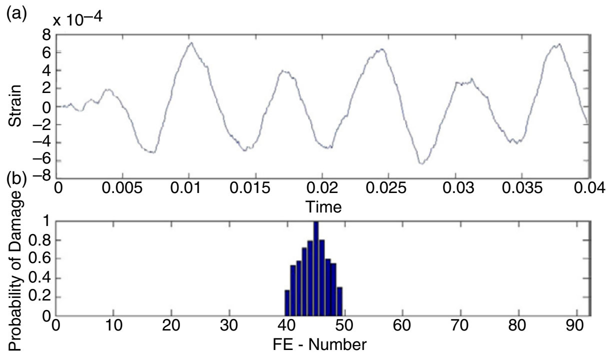

Figure 14. (a) Dynamic response in the presence of damage. (b) Damage identification.

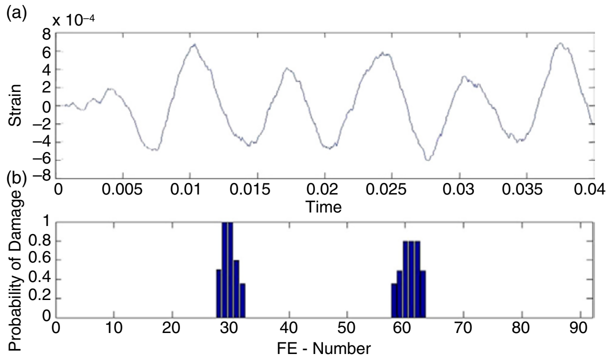

Figure 15. (a) Dynamic response in the presence of damage. (b) Damage identification.

Table 3. Retrieved cases.

Damaged element	Severity	Distance
-45-	-20%-	0.000 148 36
-46-	-20%-	0.000 148 36
-40-41-42-43-44-	-5%-5%-5%-5%-5%-	0.000 148 36
-41-42-43-44-45-	-5%-5%-5%-5%-5%-	0.000 148 36
-42-43-44-45-46-	-5%-5%-5%-5%-5%-	0.000 148 36
-43-44-45-46-47-	-5%-5%-5%-5%-5%-	0.000 148 36
-44-45-46-47-48-	-5%-5%-5%-5%-5%-	0.000 148 36
-45-46-47-48-49-	-5%-5%-5%-5%-5%-	0.000 148 36
-43-	-20%-	0.000 341 868
-48-	-25%-	0.000 341 868
-42-	-20%-	0.000 352 233
-49-50-	-15%-15%-	0.000 352 233
-48-49-50-	-10%-10%-10%-	0.000 352 233
-39-40-41-42-43-44-	-5%-5%-5%-5%-5%-5%-	0.000 352 233
-46-	-25%-	0.000 515 879

total of 102 elements: 93 for the beam and 9 for the actuator and its fixing.

The objective is to detect defects in at most five elements. A total of 5464 cases of the damaged structure have been simulated (up to 10 consecutive elements with 12 different reductions of mass), with a computation time of approximately 10 h. A total of 57 principal features have been extracted from each response signal. An SOM of 57 input neurons and $50*50$ output neurons has been trained in 35 min. Three examples are presented, two using numerical simulations and the third using experimental data from the real structure.

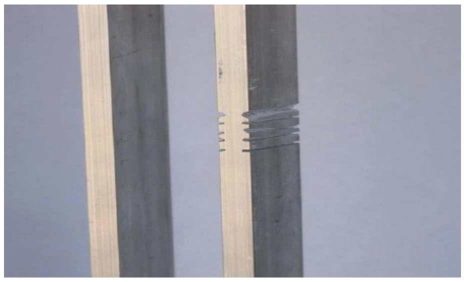

Figure 16. Original and damaged beam.

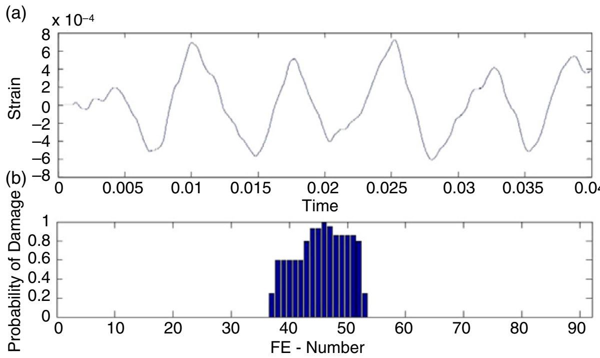

Figure 17. (a) Dynamic response in the presence of damage. (b) Damage identification.

4.1. Simulation of one fault in five consecutive elements

Damage was simulated in elements 43-44-45-46-47 with a mass reduction of 5%-15%-15%-15%-5%, respectively. The structural response is shown in figure 14(a). The retrieved cases are shown in table 3, detecting damage approximately in the assumed elements and a mass reduction of 6.7% in each element (see figure 14(b)).

4.2. Simulation of two faults in three consecutive elements

Two faults have been simulated in elements 28-29-30 and 59-60-61 with mass reductions of 20%-30%-20% and 20%-30%-20% respectively. The structural response is shown in figure 15(a). The retrieved cases are shown in table 4, showing damage detected at approximately elements 29 and 60, and a reduction in mass of 25% in each element (see figure 15(b)).

4.3. Experimental damage in unknown elements

Damage was caused to the real structure in elements 44-45-46 (see figure 16). The structural response is shown in figure 17(a). The retrieved cases are shown in table 5. We observed that this methodology detected damage in the neighbourhood of element 46 and a mass reduction of 45% (see figure 17(b)).

5. Conclusions

The feasibility of assessing structures using a knowledge-based reasoning approach has been demonstrated numerically and experimentally. This methodology performs satisfactorily in

Table 4. Retrieved cases.

Damaged element	Severity	Distance
-29-30-	-50%-50%-	0.001 3566
-60-61-62-	-30%-30%-30%-	0.001 3566
-29-30-31-	-35%-35%-35%-	0.002 6292
-28-29-30-31-32-	-25%-25%-25%-25%-25%-	0.002 6292
-60-61-62-	-35%-35%-35%-	0.002 8319
-28-29-30-31-	-30%-30%-30%-30%-	0.002 8319
-29-30-	-40%-40%-	0.002 9684
-59-60-61-62-63-	-20%-20%-20%-20%-20%-	0.003 0993
-58-59-60-61-62-63-	-20%-20%-20%-20%-20%-20%-	0.003 0993
-29-30-	-45%-45%-	0.003 3241
-61-62-	-40%-40%-	0.003 3241
-28-29-30-	-35%-35%-35%-	0.003 3241
-27-28-29-30-31-32-	-20%-20%-20%-20%-20%-20%-	0.003 3241
-59-60-61-62-	-25%-25%-25%-25%-	0.003 5077
-58-59-60-61-62-	-20%-20%-20%-20%-20%-	0.003 5077
-27-28-29-30-31-32-33-	-20%-20%-20%-20%-20%-20%-20%-	0.004 9899
-57-58-59-60-61-62-63-64-	-15%-15%-15%-15%-15%-15%-15%-15%-	0.004 9899
-26-27-28-29-30-31-32-33-34-	-15%-15%-15%-15%-15%-15%-15%-15%-15%-	0.004 9899
-56-57-58-59-60-61-62-63-64-	-15%-15%-15%-15%-15%-15%-15%-15%-15%-	0.004 9899

Table 5. Retrieved cases.

Damaged element	Severity	Distance
-38-39-40-41-42-43-	-55%-55%-55%-55%-55%-55%-	2.9403
-37-38-39-40-41-42-43-44-45-	-45%-45%-45%-45%-45%-45%-45%-45%-45%-	2.9403
-37-38-39-40-41-42-43-44-45-46-	-40%-40%-40%-40%-40%-40%-40%-40%-40%-40%-	2.9403
-44-45-46-47-48-49-50-51-52-53-	-45%-45%-45%-45%-45%-45%-45%-45%-45%-45%-	2.9403
-46-47-48-49-50-51-	-55%-55%-55%-55%-55%-55%-	2.9444
-44-45-46-47-48-49-50-51-52-	-45%-45%-45%-45%-45%-45%-45%-45%-45%-	2.9444
-38-39-40-41-42-43-44-45-46-47-	-40%-40%-40%-40%-40%-40%-40%-40%-40%-40%-	2.9444
-43-44-45-46-47-48-49-50-51-52-	-40%-40%-40%-40%-40%-40%-40%-40%-40%-40%-	2.9444
-46-47-48-49-50-51-52-	-50%-50%-50%-50%-50%-50%-50%-	2.9456
-46-47-48-49-50-51-52-53-	-50%-50%-50%-50%-50%-50%-50%-50%-	2.9456
-45-46-47-48-49-50-51-52-53-	-45%-45%-45%-45%-45%-45%-45%-45%-45%-	2.9456
-44-45-46-47-48-49-50-51-52-53-	-40%-40%-40%-40%-40%-40%-40%-40%-40%-40%-	2.9456
-46-47-48-49-50-	-60%-60%-60%-60%-60%-	2.9551
-41-42-43-44-45-46-47-48-49-50-	-40%-40%-40%-40%-40%-40%-40%-40%-40%-40%-	2.9551
-39-40-41-42-43-44-45-46-	-45%-45%-45%-45%-45%-45%-45%-45%-	2.9557
-39-40-41-42-43-44-45-46-47-48-	-40%-40%-40%-40%-40%-40%-40%-40%-40%-40%-	2.9557
-38-39-40-41-42-43-44-	-50%-50%-50%-50%-50%-50%-50%-	2.9559
-38-39-40-41-42-43-44-45-	-45%-45%-45%-45%-45%-45%-45%-45%-	2.9559
-45-46-47-48-49-50-51-52-	-50%-50%-50%-50%-50%-50%-50%-50%-	2.9559
-38-39-40-41-42-43-44-45-46-	-40%-40%-40%-40%-40%-40%-40%-40%-40%-	2.9559

locating damage and assessing its size and severity. Two of its advantages are: (1) it exploits the model of the structure to preload the casebase in the initial learning mode, and (2) in the operational mode, it incorporates new real damage cases in the casebase, improving the robustness of the methodology against errors in the model.

It is important to predetermine which damages are coherent. In theory, the casebase can be loaded with many cases but in practice there are storage limitations. Therefore, the casebase must not be loaded with defects that will never happen. Generating the cases involves a high computational cost. Building the casebase is much faster. However, it is important to note that these steps are executed once and before the system is put into operation. The retrieval and adaptation of cases to identify the defect and the feedback of the casebase (retraining the SOM) are practically immediate. Therefore, it is reasonable to conclude that this methodology can be applied to assess structures in real time.

The complexity of diagnostic tasks in structural engineering is often due to the large number of possible models for interpreting structural behaviour. For example, in a bridge, one model is the best at simulating cracks at the support but a different model is the best at simulating damage in the mid-span of the bridge. This methodology permits the simultaneous use of several models to build the casebase. In this way, it is readily adaptable for identifying different types of damage.

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