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Intelligent Agent for Damages Detection

We introduce in this paper an intelligent system that automatically detects the damage in cantilever beams called AgentMec. This agent is creating its knowledge using a database with the first ten natural frequencies of the beam damaged at pre-determined points. Using the reinforced learning, it creates the patterns to describe the behavior of the damaged beam. Then with each new vibration measurement send as input, AgentMec is able to recognize the location of the damage.

Keywords*: intelligent agent, damage, identification, vibration, frequency*

1. Introduction

Automatic detection of damage based on pre-determined analyzed vibration measurement is an important issue for modern monitoring and diagnostics of mechanical and civil engineering structures. In this paper, we propose an application of intelligent agents to the localization of damages in cantilever beams. An intelligent agent is a physical or virtual entity, which is capable of acting in an environment (e.g. the cantilever beam). Their behavioral responses are triggered by their local stimuli in this case the vibration signals coming from the accelerometers.

We will introduce here an agent called AgentMec responsible of using a continuously expanding knowledge base for an increasingly accurate determination of defects. The algorithm is learning with each measurement sample about the beam where it is acting and then after the clustering phase is able of deciding on the position of the defect.

The research is made for an unloaded cantilever beam, having a damage which reduces the cross-section with 50%. Other situations can be reduced to this case by an algorithm also developed by our research team [14].

We used, like in previous researches, a steel cantilever beam (figure 1) having the following geometrical characteristics:

- length $l = 1000$ mm
- wide $b = 50$ mm
- height $h = 5$ mm

and consequently, for the undamaged state the:

- cross-section $A = 250 \cdot 10^{-6}$ m^2,
- moment of inertia $I = 520.833 \cdot 10^{-12}$ m^4.

The chosen material parameters for the Finite Element Method-FEM simulations are in con-cordance to that of the real beam, being:

- mass density $\rho = 7850$ kg/m^3
- Young's modulus $E = 2.0 \cdot 10^{11}$ N/m^2
- Poisson's ratio $\mu = 0.3$.

This beam is considered as a reference, for beams with other dimensions (*l, b* or *h*) or mechanical characteristics (*ρ, E* or *μ*) the problem can be solved by considering the scale influence.

The paper is structure as follow: in the first section a description of the knowledge is envisaged followed in the second section by the algorithms that generate the functionalities of the agent. The third section deals with the particularities of the implementation, while in the last section we draw the conclusion based on experimental tests.

2. Description of the knowledge

The initial knowledge of AgentMec is based on the observations made in the paper [1]. There, it is presented the appearance of damages in beams as depending for each vibration mode on the shift in frequency depending on the damage location.

The knowledge base uses the first ten natural frequencies and mode shapes for the undamaged beam, as well as for eight beams with a damage placed in crucial locations. These locations were fixed on points where the amplitude for the ten modes have maximum values or are null. With each new sample added to the knowledge base the number of points can be increased.

Using the mathematical procedure from the paper [1], the first ten natural frequencies analytically calculated are given in table 1. Afterwards, the first ten natural frequencies for the undamaged beam were determined by FEM simulation; the results are presented in table 1. The FEM computation was made on 3D model beams, with a 2 mm element size. In some cases, where necessary, the damaged region was finer meshed, with 0.5 mm element size. An example of simulation to determine the natural frequency for the fifth mode is presented in figure 2.

Also, measurements on undamaged steel beam were performed. These results are also presented in table 1.

Table 1. The first ten natural frequencies

Mode i	Natural frequency f_i [Hz]		
	Analytical	FEM	Measured
1	4.076904	4.097*	4.017
2	25.549518	25.647*	24.967
3	71.539391	71.757	70.816
4	140.188654	140.63	138.053
5	231.74189	232.53	226.459
6	346.182256	347.46	338.812
7	483.510758	485.47	479.617
8	643.72734	646.59	639.138
9	826.832006	830.81	819.931
10	1032.824754	1038.1	1019.643

* corrected values of the natural frequency

As it can be observed, the results obtained in different ways fit well, varying under 3%, so that they can be interchanged between the methods. Eventually a simple calibration can be used. However, to have a natural behavior, at least the first two natural frequencies obtained with the FEM have to be corrected.

However, the mode shape indicates only the shape for each mode, without providing information about the amplitude of the displacement. Figure 3 presents the first ten vibration mode shape functions determined as in the paper [1]. Following this results we are measuring some natural frequencies for a damaged beam and subtracting the equivalent natural frequencies for the undamaged beam, in order to obtain the shift in frequency. The shift in frequency can be compared to patterns, so that it is possible to locate the damage by finding the closest pattern.

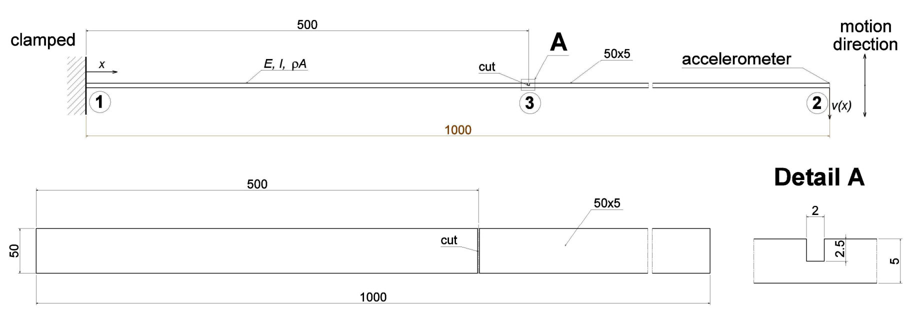

Figure 1. Cantilever beam and detail with a damage

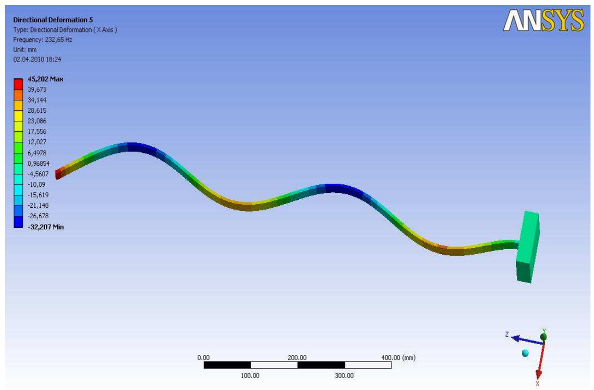

Figure 2. FEM simulation to determine the natural frequency of the fifth vibration mode

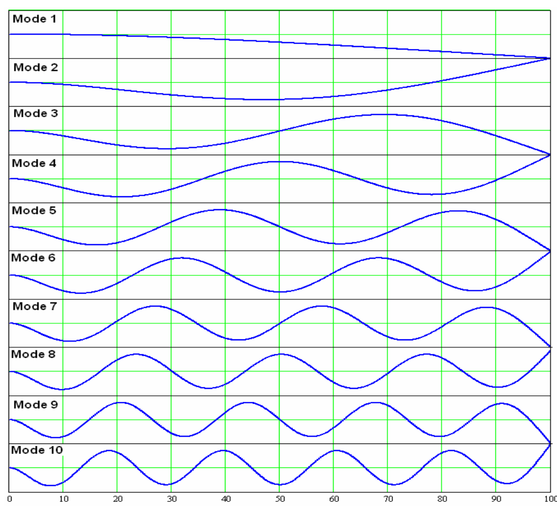

Figure 3. The first ten vibration mode shape functions

3. Functionality of the agent

In the standard reinforcement-learning model, an agent is connected to its environment via perception and action. On each step of interaction the agent receives as input, *i*, some indication of the current state, *s*, of the environment; the agent then chooses an action, *a*, to generate as output.

The action changes the state of the environment, and the value of this state transition is communicated to the agent through a scalar reinforcement signal, *r*. The agent's behavior, *B*, should choose actions that tend to increase the long-run sum of values of the reinforcement signal. It can learn to do this over time by systematic trial and error, guided by a wide variety of algorithms and we will use in this paper the Qlearning algorithm.

Formally, the model consists of:

- a discrete set of environment states, S;
- a discrete set of agent actions, A; and
- a set of scalar reinforcement signals, typically the real numbers.

It also includes an input function I, which determines how the agent views the environment state; we will assume that it is the identity function (that is, the agent perceives the exact state of the environment).

The agent's job is to find a policy, mapping states to actions, that maximizes some long-run measure of reinforcement. We expect, in general, that the environment will be non-deterministic; that is, that taking the same action in the same state on two different occasions may result in different next states and/or different reinforcement values. However, we assume the environment is stationary; that is, the probabilities of making state transitions or receiving specific reinforcement signals do not change over time. Reinforcement learning differs from the more widely studied problem of supervised learning in several ways. The most important difference is that there is no presentation of input/output pairs. Instead, after choosing an action the agent is told the immediate reward and the subsequent state, but is not told which action would have been in its best long-term interests. It is necessary for the agent to gather useful experience about the possible system states, actions, transitions and rewards actively to act optimally. Another difference from supervised learning is that on-line performance is important: the evaluation of the system is often concurrent with learning.

The Qlearning algorithms can be described as follows:

1. Set parameter ***γ****, and environment reward matrix* ***R***
2. Initialize matrix ***Q*** *as zero matrix*
3. For each new sample measurment:
4. Select random initial state
5. Do while not reach goal state
6. Select one among all possible actions for the current state
7. Using this possible action, consider to go to the next state
8. Get maximum ***Q*** *value of this next state based on all possible actions*
9.Compute ***Q****(state, action)=****R****(state, action)+* ***γ · ***max [***Q****(next state, all actions)*]
10. Set the next state as the current state
11. End Do
12. End For

The above algorithm is used by the agent to learn from experience or training. Each episode is equivalent to one training session. In each training session, the agent explores the environment (represented by Matrix R), get the reward (or none) until it reach the goal state. The purpose of the training is to enhance the 'brain' of our agent that represented by Q matrix. More training will give better Q matrix that can be used by the agent to optimally localize the defect. In this case, if the Q matrix has been enhanced, the agent will find the fastest route to the goal state.

4. Implementations issues

In the paper [1], the investigations performed, using the "Modal analysis" package in ANSYS, on damaged beams in the selected points gives the natural frequencies, the first ten for each chase of damage location being presented in table 3. This table includes also the first ten natural frequencies for the undamaged beam.

We have implemented the intelligent agent AgentMec using the MATLAB programming language. The reason for using this programming language is that it is very easy to develop prototypes and has an advanced interface for recording the accelerometer data. At the beginning the implementation was done using simple interpolation. In other words, the if-then rules of the agent were considered as categorical (as in an ideal situation with no uncertainty). In a second phase, we consider using fuzzy logic to model uncertainty in the decision process. In this case, the knowledge base consists of fuzzy rules.

The R matrix with the environment is given by the accelerometer data and the Q matrix used as 'brain' is given in the table 3 and 4.

The values for the first ten vibration modes (i = 1 … 10) and the eight values of *Dk* from table 2 were calculated and are presented in matrix form in table 4 and in a graphical way in figure 4. It has to be mentioned that in figure 5 only the values of mode are displayed.

Table 2. Damage location for the eight kind of damaged cantilever beams

Distance to the clamped end [mm]							
0	214	358	500	644	783	868	906

Table 3. First ten vibration modes for damaged beams

Dk	Frequency $f_{i\text{-}Dk}$ [Hz] for the corresponding mode *i* and location of the damage *Dk* or without damaged *U*									
[mm]	$f_{1\text{-Dk}}$	$f_{2\text{-Dk}}$	$f_{3\text{-Dk}}$	$F_{4\text{-Dk}}$	$f_{5\text{-Dk}}$	$f_{6\text{-Dk}}$	$f_{7\text{-Dk}}$	$f_{8\text{-Dk}}$	$f_{9\text{-Dk}}$	$f_{10\text{-Dk}}$
0	3,931	24,69	69,31	136,11	225,46	337,48	472,26	629,86	810,2	1013,2
214	3,988	25,63	71,09	137,91	229,69	347,08	483,44	634,94	814,5	1029,5
358	4,035	25,34	70,57	140,63	228,23	342,96	484,9	633,49	824,4	1033,5
500	4,066	25,01	71,75	137,48	232,52	339,97	485,45	633,12	830,7	1016,7
644	4,084	25,13	70,26	140,63	228,38	342,89	484,99	633,68	823,9	1034,3
783	4,092	25,47	70,25	137,03	229,46	347,18	482,94	634,58	816,1	1032,1
868	4,095	25,60	71,28	138,42	226,99	338,64	475,81	639,39	828,1	1038,1
906	4,096	25,63	71,61	139,7	229,49	340,59	473,72	630,6	812,8	1021,2
U	$f_{1\text{-U}}$	$f_{2\text{-U}}$	$f_{3\text{-U}}$	$f_{4\text{-U}}$	$f_{5\text{-U}}$	$f_{6\text{-U}}$	$f_{7\text{-U}}$	$f_{8\text{-U}}$	$f_{9\text{-U}}$	$F_{10\text{-U}}$
	4,09*	25,6*	71,75	140,63	232,53	347,46	485,47	646,59	830,8	1038,1

* corrected values of the natural frequency

Table 4. Relative shift in frequency for the damaged beams

Dk	Relative shift in frequency $\Delta f_{i\text{-}Dk}$ [%] for the corresponding mode *i* and location of the damage *Dk*									
[mm]	$\Delta f_{1\text{-Dk}}$	$\Delta f_{2\text{-Dk}}$	$\Delta f_{3\text{-Dk}}$	$\Delta f_{4\text{-Dk}}$	$\Delta f_{5\text{-Dk}}$	$\Delta f_{6\text{-Dk}}$	$\Delta f_{7\text{-Dk}}$	$\Delta f_{8\text{-Dk}}$	$\Delta f_{9\text{-Dk}}$	$\Delta f_{10\text{-Dk}}$
0	0,165	0,948	2,448	4,520	7,070	9,980	13,210	16,730	20,530	24,900
214	0,109	0,015	0,661	2,720	2,840	0,380	2,030	11,650	16,240	8,600
358	0,062	0,301	1,180	0,000	4,300	4,500	0,570	13,100	6,410	4,600
500	0,030	0,630	0,002	3,150	0,010	7,490	0,020	13,470	0,080	21,400
644	0,012	0,512	1,489	0,000	4,150	4,570	0,480	12,910	6,840	3,800
783	0,004	0,173	1,502	3,600	3,070	0,280	2,530	12,010	14,670	6,000
868	0,002	0,044	0,658	2,210	5,540	8,820	9,660	7,200	2,740	0,000
906	0,001	0,013	0,151	0,930	3,040	6,870	11,750	15,990	17,940	16,900

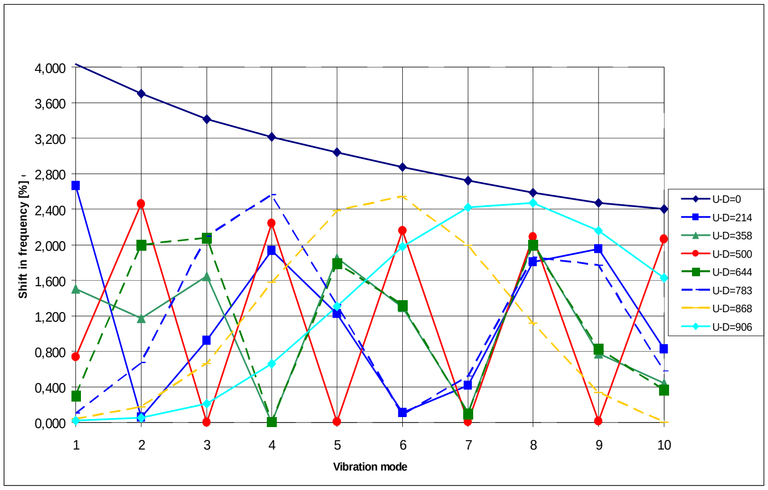

Figure 4. The relative shift in natural frequency for the first ten vibration modes and eight types of damage

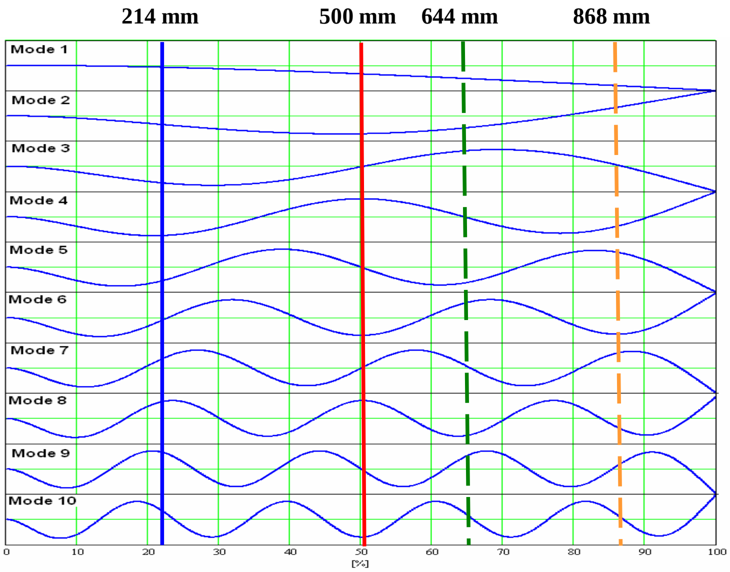

Figure 5. The first ten vibration mode shape functions and the shift in frequency for four types of damage

5. EXPERIMENTAL CASE AND CONCLUSIONS

For the experiments we have considered the damages to have a depth of 2.5 mm, and consequently reduce the cross-section of the beam with 50%. The beam with a damage on the clamped end (D = 0 mm) is presented in figure 6.

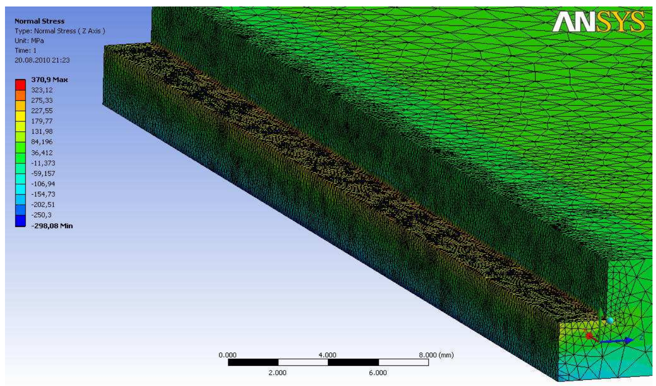

Figure 6. Stress distribution at the clamped end for a beam with a damage reducing to half the cross-section

For this test AgentMec which permits an automatic location of damages in cantilever beams. The reinforced learning algorithm will compare measurement results with patterns describing the dynamic behavior of a beam with damages placed on various locations along it. The acting is done as in the figure 7 and figure 8.

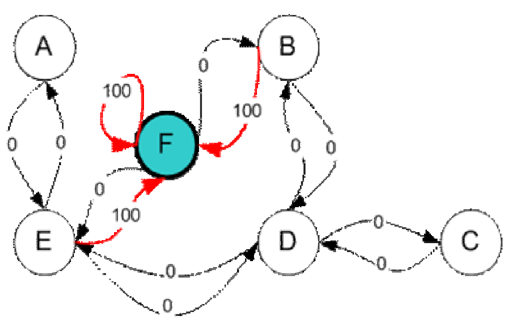

Figure 7. Learning phase in which it creates the graph with the knowledge.

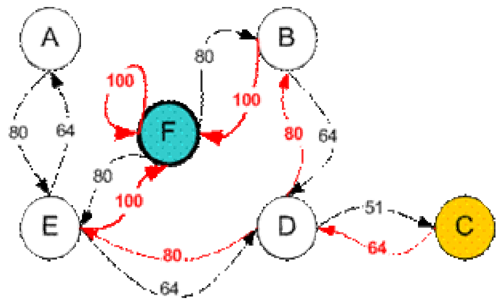

Figure 8. Decision phase in which it localizes the damage.

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