A CO-EVOLUTIONARY STRATEGY FOR STRUCTURAL DAMAGE IDENTIFICATION

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ABSTRACT

A new methodology for damage identification is presented in this work. This new strategy, called the Estimation-Exploration Algorithm (EEA) is designed to identify damage using a minimum number of physical tests. The underlying dynamics of the algorithm mimic the principles of co-evolution in which different populations of individuals challenge each other in an ongoing cycle of adaptation. In the context of structural damage identification, two main populations exist: a population of damage hypotheses and a population of potential physical tests. Damage hypotheses are evolved to predict data collected from physical tests, while the population of tests evolves to create discrepancy among the best current damage hypotheses. This competition results in a sequence of tests that drives the damage hypotheses towards the global optimum solution. The feasibility of the methodology has been demonstrated in numerical simulations. EEA has demonstrated greater accuracy in identifying damage than alternate strategies such as random selection of tests and user-designed tests.

KEYWORDS

Genetic algorithms, damage identification, optimal testing, health monitoring, co-evolution

INTRODUCTION

One of the main challenges in structural health monitoring is to obtain sufficient information through sensing so that damage identification algorithms can uniquely and unambiguously characterize the current state of the structure. Information (e.g. displacement or acceleration histories) obtained from a structure is usually limited due to the use of a small number of sensors. Even when a large number of sensors are used, the information may still be incomplete due to the inability of the sensor network to perceive damage in certain regions of a structure. The amount of information about damage in a structure can be increased by performing a sequence of strategic tests composed of actuation and sensing. However, a significant challenge that engineers constantly face in non-destructive evaluation is how to perform these strategic tests so as to maximize the likelihood of finding damage with the least number of trials.

A co-evolutionary strategy is presented herein which minimizes the number of tests needed for solving inverse problems that arise in structural health monitoring applications (Kouchmeshky et al. 2006). A co-evolutionary paradigm is used to setup competition between tests and damage scenarios with the ultimate goal of eliminating false

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hypotheses and identifying a near optimal solution. The proposed algorithm is composed of two stages: an estimation phase, which searches for damage scenarios that can predict current physical tests, and the exploration phase, which searches for tests that increase the level of information about the damaged system. Evolutionary algorithms are used to implement the two stages of the proposed strategy.

Co-evolution is a biological process where populations of interacting individuals challenge each other in an ongoing cycle of adaptation. There has been growing interest in co-evolutionary algorithms within the evolutionary computation community, starting with the seminal work of Hillis (1992) on sorting networks. Contrary to conventional evolutionary systems, in which individuals are evaluated using a static quality or fitness metric, co-evolutionary systems consist of one or more populations in which individuals may influence the relative ranking of each other (Bucci et al. 2004).

THE ESTIMATION-EXPLORATION ALGORITHM (EEA)

The problem of damage identification is concerned with existence, location, and severity of the damage in a structure. When damage identification is cast as an optimization problem, great challenges arise such as large search domains and lack of sufficient information from tests performed on the structure. This leads to ill-posed inverse problems in which solution uniqueness is not guaranteed. The naïve way of getting around this situation is to continue to test the structure until enough information can be extracted. However, apart from the cost, blind testing may fail to elucidate sufficient information about the damage state of the structure, even if a very large number of tests are carried out.

The Estimation-Exploration Algorithm (EEA) presented in this work is designed to search for the global optimum solution with the least number of physical tests. The steps involved in EEA are summarized in Figure 1. Two main stages are involved in this algorithm: the estimation phase and the exploration phase. In the estimation phase, candidate solutions are sought based on information gained from current tests. This step is similar to conventional structural damage identification approaches. In the early stages of EEA, multiple candidate damage scenarios will be obtained due to the ill-posedness of the inverse problem. In the exploration phase, a set of the best candidate solutions found in the estimation phase are used to select the next test to be performed on the structure. The exploration phase is cast as an optimization problem in which the objective is to maximize the discrepancy among candidate damage scenarios. Maximizing the discrepancy among candidate damage scenarios can be interpreted as increasing information about the state of the structure since the selected candidate solutions can already explain all the existing test data.

FORMULATION

The steps involved in EEA will be described in the context of structural damage identification in truss structures subjected to static loading. The methodology however is general and has been applied to dynamics problems (Kouchmeshky and Aquino, 2006). Static response simplifies the theoretical framework for demonstrating the feasibility of proposed algorithm. In addition, static tests eliminate uncertainties related to insufficient knowledge about the damping and mass distribution in the structure as is the case in vibration tests.

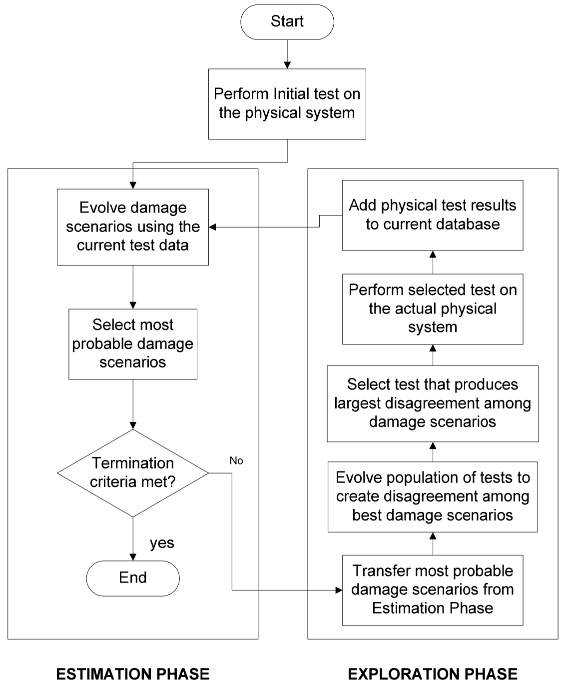

Figure 1. Flowchart of the Estimation-Exploration Algorithm. (Figure 1 in (Kouchmeshky et al.)).

Local damage in truss elements can result, for instance, from the decrease of cross sectional area due to cracking or corrosion, which will translate into the reduction of the global stiffness of the structure. For the skeletal structures studied in this paper, the mathematical model for the system can described as

$$\mathbf{K}(\boldsymbol{\alpha})\mathbf{u} = \mathbf{f}, \qquad (1)$$

where $\mathbf{K}(\boldsymbol{\alpha})$ is the stiffness matrix of the structure defined as a function of a vector of damage parameters $\boldsymbol{\alpha}$, $\mathbf{f}$ represents the load applied to the structure, and $\mathbf{u}$ are the computed displacements at all degrees of freedom. There is one damage parameter, α, per element of the truss that represents the relative decrease in stiffness of that element. The reduced stiffness, $\mathbf{K}^{ee}{}_{i}$, corresponding to element i in the structure can be computed from the undamaged stiffness, $\mathbf{Ko}^{ee}{}_{i}$, and the corresponding damage parameter, α_i, as

$$\mathbf{K}^{ee}{}_{i} = (1-\alpha_i)\mathbf{Ko}^{ee}{}_{i}. \qquad (2)$$

The global stiffness matrix is assembled from individual element contributions as

$$\mathbf{K}(\boldsymbol{\alpha}) = \sum_{elements} \mathbf{K}^{ee}{}_{i}. \qquad (3)$$

Damage parameters are obtained by minimizing the error between the computed response and the measured displacements. The error function used in this article is given by

$$E(\boldsymbol{\alpha}) = \frac{1}{n}\sum_{j=1}^{n}\left\|\frac{\mathbf{u_c}^j - \hat{\mathbf{u}}^j}{\max\left(\hat{\mathbf{u}}^j\right)}\right\|, \qquad (4)$$

$$\mathbf{u_c}^j \subset \mathbf{u}^j$$

where n is the number of tests performed on the structure, j indexes the tests, $\mathbf{u}^j_{\mathbf{c}}$ is a vector whose elements are the computed displacements at sensor locations, and $\hat{\mathbf{u}}^j$ is a vector containing the measured displacements. The difference between displacements should be normalized to get a better representation of the relative change in response. The maximum displacement of all sensors is selected as the normalization parameter to cancel out spurious effects of very small displacements. The damage parameters, $\boldsymbol{\alpha}$, are obtained by solving the following optimization problem.

$$\underset{\boldsymbol{\alpha}\in\mathbb{R}^m}{\mathit{Minimize}}\ E(\boldsymbol{\alpha}) \qquad \text{Subject to } 0 \le \alpha_i \le 1 \quad (5)$$

ESTIMATION PHASE

The estimation phase consists in finding candidate models that minimize the error between the predicted response and the tests that have been carried on the structure so far. In our work, the fitness of each individual is defined as the negative of the output error. The following fitness function is used in the estimation phase.

$$f = -E(\boldsymbol{\alpha}) \qquad (6)$$

The population of solutions is evolved for a given number of generations and the best z candidate damage scenarios are transferred to the exploration phase (i.e. selection of tests). Where z is a number defined by the user and represents the number of candidate solutions that will be used for selecting the next test.

The genetic algorithm used in the estimation phase used a special encoding which has been shown to be very efficient (Kouchmeshky et al.) for structural damage identification problems. In this approach, two strings of real numbers were used for encoding damage. The first string encodes the damage parameters, α_i, for all elements, while the second string is used to determine whether or not damage is present in a given element. For a more detailed description of this encoding see (Kouchmeshky et al.).

Maintaining diversity in the solution population is crucial for the success of EEA. For this purpose a hybrid approach was used, which combines the deterministic crowding method (Mahfoud, 1996) with fitness sharing. Other genetic operators used included single-point crossover, and mutation.

EXPLORATION PHASE

The goal of the exploration phase is to find a test that maximizes discrepancy among candidate solutions (i.e. damage scenarios) selected from the estimation phase. This task is cast as an optimization problem, which is solved using a genetic algorithm. The fitness of a test in the exploration phase is proportional to its ability to create disagreement among candidate solutions. The fitness function for tests used in this work is defined as

$$f_{test} = 100 \cdot \sum_{b=1}^{mdof} \sqrt{\frac{1}{z}\sum_{a=1}^{z}\left[\frac{u_{ab} - \bar{u}_b}{u_{\max}}\right]^2}\,, \qquad (7)$$

where z is the number of candidate solutions transferred from the estimation phase, u_{ab} is the displacement at degree of freedom b corresponding to model a, $\bar{u}_b$ is the average displacement obtained from the candidate models at degree of freedom b, $u_{\max}$ is the maximum displacement computed from all models, and $mdof$ is the number of degrees of freedom where displacements are measured. Equation (7) is in essence the summation of the standard deviations of displacement at each degree of freedom for all selected models. It is important to keep in mind that selected candidate solutions can predict the data collected from the tests performed so far. Therefore, by creating discrepancy among candidate solutions, hidden information about the state of the damage structure is revealed.

The population of tests is randomly generated at the beginning of the exploration phase. Then, selection, crossover, and mutation are applied over a number of generations. At the end of the evolution process, the test genome with the highest fitness is selected and is implemented in a physical experiment. Results of this experiment are added to the existing bank of tests and the estimation phase is invoked for the next cycle of the algorithm.

Different strategies may be adopted for encoding tests during the exploration phase. These strategies depend on the type of excitation (e.g. static vs dynamic tests) and quantities being measured. For instance, in the case of static loads, a test may be defined by the number of forces applied to the structure, the direction, location and magnitude of the forces, the number of degrees of freedom being measured, and the location of the sensors. Whatever test definition is used, an important issue to always consider is the conservation of building blocks in the encoding scheme in order to maximize the effectiveness of the evolution process. For instance, the encoding should assure that blocks of sensors and forces are transferred between individuals during crossover. The reason for this is that sensor locations that can detect localized damage depend on the forces acting on the structure.

TERMINATION CRITERIA

The proposed algorithm terminates when one of these conditions is met.

- One individual can explain all tests in a predefined number of consecutive cycles. This indicates that a potentially good solution has been found.
- Diversity is not maintained. At least two different individuals need to be transferred from the estimation phase to the exploration phase. Loss of diversity may be due to various factors such as inadequate parameters in the niching method, size of the population, number of generations, etc.
- The exploration phase cannot find a test that causes disagreement among candidate solutions. In this case, the algorithm cannot single out a unique solution. This situation may indicate that the problem is not fully observable.

NUMERICAL EXAMPLES

The feasibility of the methodology is demonstrated with several numerical examples. A four-span bridge truss (Figure 2) with 105 elements and 44 nodes and subjected to static loading was used in all the examples. The area selected for the elements of the truss was 2500 mm^2 and the Young's modulus of the material was 200 GPa. Five damaged elements localized in the first left bay were introduced in the structure. The level of damage induced in these elements is shown in Table 1.

In addition to the proposed method (EEA), a control algorithm was used in which the exploration phase was disabled and random tests were used instead. Also, a case where tests were designed by the authors was investigated. In this case, 10 structural tests were engineered so that all bays were tested and loads and sensors were kept in close proximity to maximize the measured response. For this case, the damage identification process was carried using all the data collected from the tests at once as it is a common procedure found in the literature. The control algorithm and the engineered tests serve as a benchmark to determine whether the proposed co-evolutionary strategy has significant advantages over these alternate approaches.

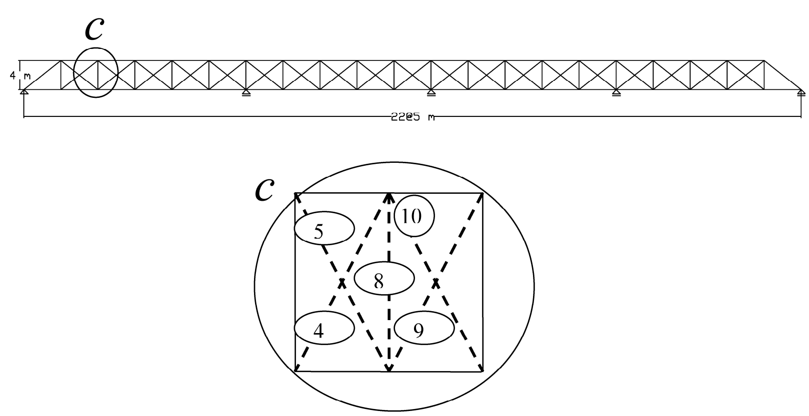

Figure 2. Truss used in numerical examples. Dashed lines represent damaged elements. (Figure 4 in (Kouchmeshky et al.))

Each test encoded the locations of three loads applied in the vertical direction at nodes in the bottom cord of the truss along with the locations of a fixed number of sensors also in the bottom cord. In addition, in order to study the sensitivity of EEA to noise, uniformly distributed random noise was added to measurements in the simulated tests as

$$\hat{u}^j = \hat{u}_o{}^j \left(1+\beta e\right), \qquad (8)$$

where $\hat{u}_o{}^j$ is the measured displacement at degree of freedom j without noise, β is the noise amplitude, and e is a uniformly distributed random variable in the range [-1,1].

Table 1: Damge Ratios used in truss example (Table I in (Kouchmeshky et al.))

Element Label	Damage Ratio, α
4	0.40
5	0.25
8	0.10
9	0.20
10	0.30

The performance of each strategy was evaluated by considering its accuracy in identifying the damage elements, accuracy in estimating the damage index for each element, and the number of misidentifications produced. A misidentification is defined as a non-damaged element for which the algorithm produces an average damage index greater than zero.

The results obtained from the different strategies (EEA, control, and engineered tests) are summarized in Figures 3-5. These plots show the average damage indexes found in each element as well as their standard deviation over ten computer runs. Figures 3 shows that EEA was able to find accurately and consistently all damage elements and their damage indexes at the end of 10 cycles. In addition, it produced no misidentification. Notice that only Element 8 presents some scatter in the results.

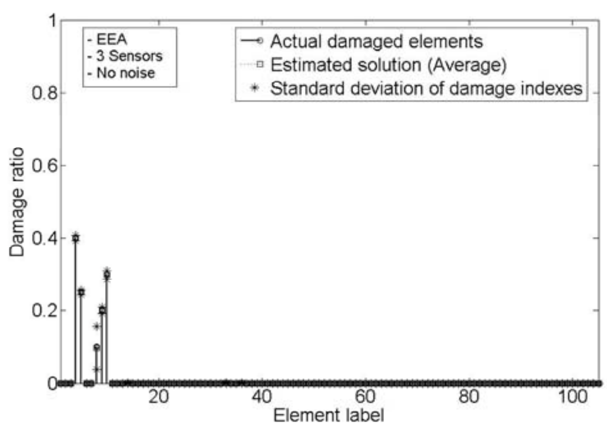

Figure 3. Damage indexes found using EEA after 10 cycles. No noise. (Figure 5 in (Kouchmeshky et al.)).

Figure 4 shows the results obtained when 10 engineered tests were used for the damage identification process. It can be noticed in this figure that the five damaged elements were correctly identified on average, but the EEA results were considerably more accurate in terms of the damage indexes. Notice also the larger scatter in the results obtained using engineered tests. There are several possible reasons for the superior performance of EEA over engineered tests. For instance, data in the engineered tests is presented all at once (as is common practice) to the damage identification algorithm, resulting in a more complex optimization problem. Also, EEA selects tests using a strategy devised for elucidating new information in each test, while engineered tests may contain redundant information.

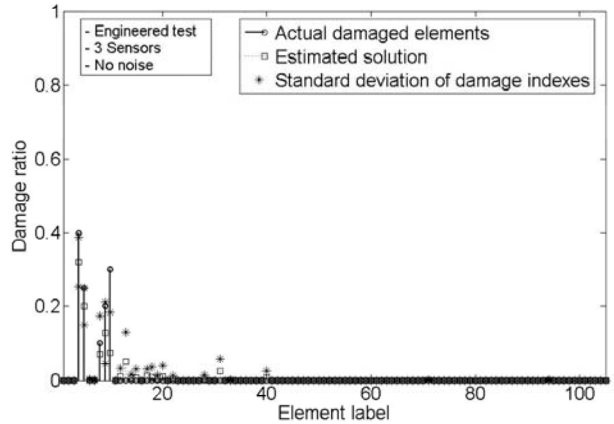

Figure 4. Damage indexes found using engineered tests after 10 cycles. No noise (Figure 6 in (Kouchmeshky et al.)).

Figure 5 shows the results obtained using the control algorithm in which location of sensors and forces in each test were generated randomly. It can be observed that although the five damaged elements could be found, the accuracy of the damage indexes is less than that observed for the solutions obtained by EEA and the engineered tests strategy. In addition, the results obtained by the control algorithm show a larger scatter and more misidentifications than those obtained with the other strategies. The poorer performance of the control algorithm is due to the random nature of the test selection.

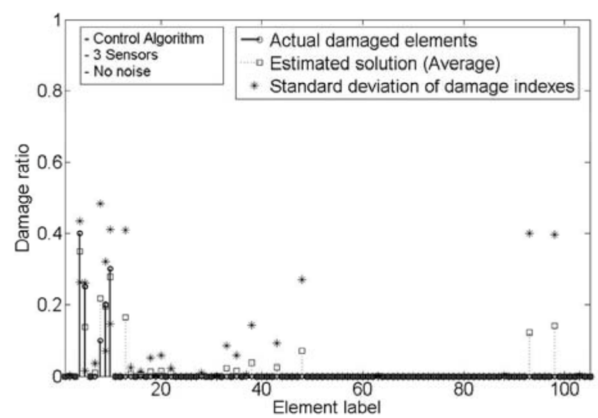

Figure 5. Damage indexes found using control algorithm after 10 cycles. No noise (Figure 7 in (Kouchmeshky et al.)).

The performance of EEA, the engineered tests strategy, and the control algorithm in the presence of noisy data are depicted in Figures 6-8. It can be seen from these plots that noise decreases the accuracy of the algorithms and increases the scatter in the results as expected. Although the three strategies (EEA, control, and engineered tests) were able to locate the five damage elements, EEA was the most accurate in estimating the damage indexes and producing the fewest misidentifications. The control algorithm, as expected, produced the worst results, which can be attributed to the random test selection process as explained before.

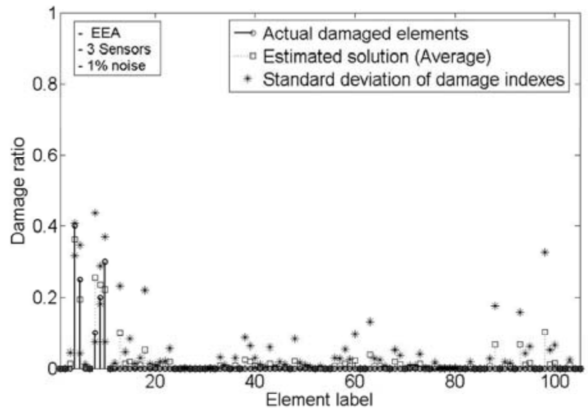

Figure 6. Damage indexes found using EEA after 10 cycles. 1% noise. (Figure 11 in (Kouchmeshky et al.))

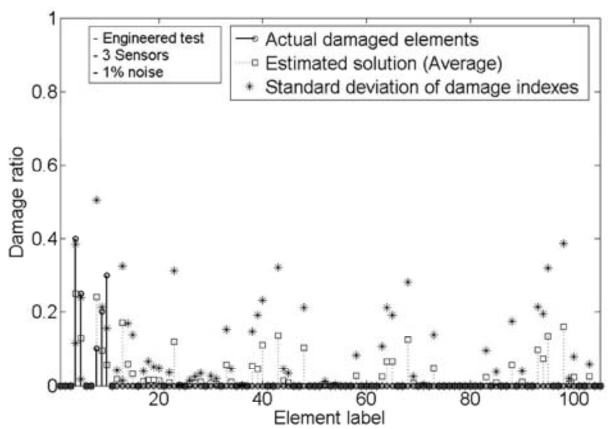

Figure 7. Damage indexes found using engineered tests after 10 cycles. 1% noise. (Figure 12 in (Kouchmeshky et al.))

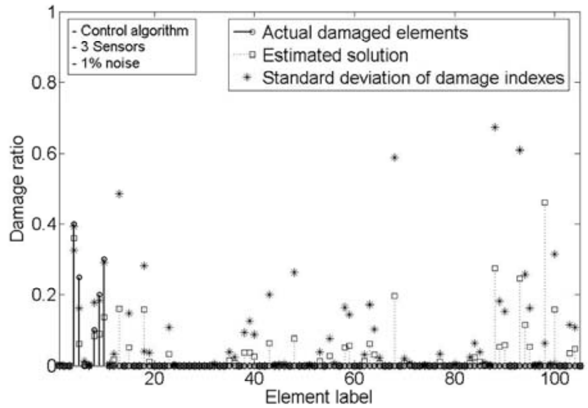

Figure 8. Damage indexes found using the control algorithm after 10 cycles. 1% noise. (Figure 13 in (Kouchmeshky et al.))

CONCLUSIONS

A new co-evolutionary algorithm for structural damage identification has been presented. The algorithm is composed of two stages: the estimation phase that searches for damage scenarios and the exploration phase, which searches for tests that increase the level of information about the damage system.

The feasibility of the methodology was demonstrated through several numerical examples. The proposed algorithm was compared to two alternate strategies: a control algorithm in which the exploration phase was disabled and tests were generated randomly, and a strategy in which tests were engineered by the authors. EEA outperformed the control algorithm and the engineered tests strategy by displaying higher accuracy in identifying damage indexes and producing fewer misidentifications. In addition, the results obtained with EEA contained less scatter than those obtained with the two alternate methodologies.

REFERENCES

Bucci, A., Pollack, J. B., and De Jong, E. D. (2004). "Automated extraction of problem structure." *Proceedings of the Genetic and Evolutionary Computation Conference*, 501–512.

Hillis, W. D. (1992). "Co-evolving parasites improve simulated evolution as an optimization procedure." *Artificial Life II*.

Kouchmeshky, B., and Aquino, W. (2006). "Structural Damage Identification Using Co-Evolution and Frequency Response Functions." *Computers & Structures, in review*.

Kouchmeshky, B., Aquino, W., Bongard, J. C., and Lipson, H. (2006). "Co-evolutionary Algorithm for Structural Damage Identification Using Minimal Physical Testing." *International Journal for Numerical Methods in Engineering, in review*.

Mahfoud, S. W. (1996). "Niching methods for genetic algorithms," Ph.D., University of Illinois at Urbana-Champaign, Urbana, IL.