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DATA DRIVEN METHODOLOGY BASED ON ARTIFICIAL IMMUNE SYSTEMS FOR DAMAGE DETECTION·

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ABSTRACT

Structural Health Monitoring is a growing area of interest given the benefits obtained from its use. This area includes different tasks in the damage identification process, the main important, is the damage detection since an early detection allows to avoid possible catastrophes in structures in service. Practical solutions require a big quantity of sensors and a robust system to process and obtain a reliable solution. In this sense, bio-inspired algorithms provide tools for an effective data analysis taking advantage of the developments provided by the nature by means of computational algorithms.

As a contribution in this area, this paper presents a methodology for structural damage detection using a type of artificial intelligence that is called artificial immune system. The developed methodology includes the inspection of the structure by means of a distributed piezoelectric active sensor network at different actuation phases to define a baseline by each actuation phase using data from the structure when it is known as healthy. In a second step, same experiments are performed to the structure when its structural state is unknown to determine the presence of damage by using the developed artificial immune system. Results show that the proposed methodology allows to detect damages in the experimental setup.

KEYWORDS : *artificial immune system, damage detection, affinity values.*

INTRODUCTION

Damage detection is an important issue in *structural health monitoring* (SHM), since it provides some basic tools for a future and more detailed damage analysis such as localization and classification of damages. To achieve this objective, different methodologies have been developed. However, among the big quantity of developments, the use of bio-inspired algorithms has proven good results due to the robustness that it adds to the task where it is applied. This paper, presents the use of a bio inspired approach that is based on *artificial immune systems* (AIS) to detect damages in a structure that is instrumented with a piezoelectric system.

The use of AIS as a data-driven application is relatively new and, compared with the application of other approaches in SHM, there is a reduced number of works. In the literature, it is possible to find the following works in the field of detection and classification of damages and faults. In 2003, Costa et al. [1] developed three module algorithms called *T*-module, *B*-module and *D*-module. These are based on immunologic principles in order to detect anomalous situations in a squirrel-cage motor induction motor. The *T*-module distinguishes between self- and non-self-conditions, the *B*-module analyzes the occurrence of both cells (self and non-self) and finally *D*-module is a simple

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systems that reports some unusual condition to a central unit, as a candidate anomaly. In the work of Costa et al., the normal operation condition of the machine (self) is represented by the frequency spectrum, which can include harmonics or not. In 2008, Zhang et al. [2] used a clonal selection algorithm for solving a combinatorial optimization problem called sensor optimization. This problem consists in choosing an appropriate distribution of a set of sensors in a structure in order to detect impacts. In this work, the authors tested a composite plate instrumented with 17 piezoceramics transducers (PZT). In 2010, Chen [13] applied an agent-based artificial immune system for adaptive damage detection. In this approach, a group of agents is used as immune cells (*B*-cells) to patrol over a distributed sensor network (installed in the structure) and the damage diagnosis are based on the analysis of structural dynamic response data. Each mobile agent inspects the structure based on agent-based cooperation protocols. In 2011, Chen and Zang [2] presented an algorithm based on immune network theory and hierarchical clustering algorithms. Chilengue et al. [4] presented an AIS approach for the detection and diagnosis of failures in the stator and rotor circuits of an induction machine. In the approach, the machine dynamic is compared before and after the fault condition; the Clarke transformation was also applied to the stator current in order to obtain a characteristic pattern of the machine, which is finally applied to the pattern recognition algorithm. More recently, in 2012, Zhou et al. [5] —inspired by the Chen's work—, developed a classifier of damage in structures based on the immune principle of clonal selection. Using evolution algorithms and the immune learning, a high quality memory cell is generated in the classifier to recognize several damage patterns in structures. In 2012, Xiao [6] developed a structural health monitoring and fault diagnosis system based on artificial immune system. In Xiao's approach, the antigen represents the structural state (healthy or damaged), whereas the antibody represents database information that identifies a damage pattern. In that work, the features space is built by natural frequencies and modal shapes obtained by simulation of the structure in free vibration and seismic response. This paper presents a different point of view by defining a special feature vector by taking advantage of the main features of the immune system to detect abnormal situations and to define them as a possible damage. This paper is organized as follows: Section 1 presents a theoretical background with the most basic information about the natural immune systems and its equivalent in an artificial system. Section 2 presents the experimental setup used to validate the methodology. Section 3 presents the methodology and the results. Finally, some conclusions are drawn.

1. THEORETICAL BACKGROUND

This section presents a brief introduction to the different concepts and methods used in the methodology presented on this paper. More detailed information can be consulted in the references includes in this section.

1.1 Human immune systems

The human immune system is a complex and robust defense mechanism composed by a large network of specialized cells, tissues and organs. The system further includes an elevated number of sensors and a high processing capability. This system has shown its effectiveness in the detection of foreign elements by protecting the organism against disease. Among its skills are: to distinguish between its own cells (self) and foreign cells (non-self), to recognize different invaders (called antigen) in order to ensure the protection of the body and to learn from specific antigen and adapt to them in order to improve the immune response to this kind of invader.

To protect the organism, this system has different defense levels such as external barriers, innate immune system and adaptive immune system. The first concerns the major line of defense into the human body and includes elements such as the skin, the mucus secreted by the membranes, the tears, saliva and urine which present different physiological conditions that are harmful to the antigens as the temperature and the pH level, among others. The response of these barriers is equal

for any foreign invader [7]. The second owes its name to the fact that the organism born has the ability to recognize certain antigens and destroy them immediately on first encounter. This barrier acts when the first barrier is broken and this immunity is unchanging [8]. The last barrier is the final defense level and responds to the stimulus of foreign cells or antigens that evade both the external barriers and the innate immune defense [8]. This stimulus provides the capability of learning into the immune system. This way, in a future detection of this antigen, the system knows how to proceed. The immune systems also includes different type of cells, some of these are cells born in the bone marrow and usually called white blood cells [9]. Among the white blood cells it is possible to highlight the *T*-cells and the *B*-cells. The *T*-cells are called so because their maturation takes place in the thymus, they have high mobility and can be found in the blood and the lymph [10]. The *B*-cells produce and secrete a special protein called antibody, which recognizes and binds the antigen. Each *B*-cell is the responsible to produce a specific antibody. This protein is used for signaling other cells to remove them from the body [10]. The *T*-cells and the *B*-cells proliferates when they recognize antigens and, some of them, become memory cells that remain in the immune system in order to eliminate the same antigen in the future in a more effective manner [10], [9].
Three immunological principles are used in artificial immune system [10], [9]:
-Immune network theory: This theory explains how the immune memory is built by means of the dynamic behavior of the immune system cells. These cells can recognize by themselves, detect invaders, as well as interconnect between them allowing the stabilization of the network [8].
-The negative selection: The negative selection is a process that allows identifying and removing cells that react to the own body cells giving to the system a tolerance to own cells. This ensures a proper functioning of the immune system since it is able to distinguish between foreign molecules and self-molecules, avoiding autoimmune diseases [9].
-The clonal selection: This is a process of adaptive immune responses in which the cells of the system are adapted to identify an invader element [10]. Antibodies capable of recognizing an antigen can proliferate and the rest are eliminated. The new cells are clones of their parents and they are subjected to an adaptation process by mutation. From the new antibody set, the cells that have the greatest affinity with the primary antigen are selected as memory cells and the remainders are eliminated.

1.2 Artificial immune systems

Artificial immune system (AIS) is an adaptive and bio-inspired computational system based on the processes, performance of the human immune system and its properties such as diversity, error tolerance, dynamic learning, adaptation, distributed computation and self-monitoring [11]. Nowadays, this computational system is used in several research areas such as pattern recognition [14], optimization [10], among others [2]. Table I presents the analogy between the natural and artificial immune systems.

Table I. Analogy between the biological immune system and artificial immune system [6]

Biological immune systems (BIS)	**Artificial immune systems (AIS) in structural health monitoring (SHM)**
antibodies	a detector of a specific pattern
antigens	structural health or damage condition
the matured antibodies	database or information system for damage detection
recognition of antigens	identification of health and damage condition
Process of mutation	training procedure
immune memory	memory cells

In the implementation of an artificial immune system, it is necessary to bear in mind three important aspects: First of all, it is necessary to define the role of the antigen and the antibody in the context of the application. Generally, an antigen is the solution to be achieved, for instance when it is necessary to check the data to know if it is an intrusion, or the element to classify, while the antibodies are the remaining data or those that have been previously identified [15]. Both antigens (**Ag**) and antibodies (**Ab**) are represented or coded in the same way; this representation is generally given by a string of binary or real numbers. A second important aspect is to define the mechanism by which the degree of correspondence between **Ag** and **Ab** molecules is measured. This measure is related to the distance between them [18]. Finally, there exists the adaptation process of the molecules in the artificial immune system. This adaptation allows including the dynamic of the system, for instance, the antibodies excitation, cloning all the excited antibodies and the interconnection between them. All these elements are adapted from the three immunologic principles previously introduced.

1.3 Principal Component Analysis

PCA is a classical method used in statistical multivariate analysis, feature extraction and dimensionality reduction. The general idea in the use of PCA is to find a smaller set of variables with less redundancy but with a minimal loss of information [16]. The application of PCA starts with a matrix $\mathbf{X}$ which contains information from m sensors and n experimental trials [12]. Since the data organized in this matrix come from experimental trials and could have different magnitudes and scales, it is necessary to apply a preprocessing step to scale the data using the mean of all measurements of the sensor at the same time and the standard deviation of all measurements of the sensor. Using this preprocessed matrix it is possible to calculate the covariance matrix as follows:

$$\mathbf{C_X} \equiv \frac{1}{n-1}\mathbf{X}^T\mathbf{X} \tag{1}$$

$\mathbf{C_X}$ is a square symmetric $m \times m$ matrix that measures the degree of linear relationship within the data set between all possible pairs of variables (sensors). The subspaces in PCA are defined by the eigenvectors and eigenvalues of the covariance matrix as follows:

$$\mathbf{C_X}\tilde{\mathbf{P}} = \tilde{\mathbf{P}}\Lambda, \tag{2}$$

where the eigenvectors of $\mathbf{C_X}$ are the columns of $\mathbf{P}$ and Λ is a diagonal matrix whose diagonal elements are the eigenvalues and the off-diagonal terms are zero. The columns of matrix $\tilde{\mathrm{P}}$ are sorted according to the eigenvalues by descending order and they are called principal components of the data set. Choosing only a reduced number $r < n$ of principal components, those corresponding to the first eigenvalues, the reduced transformation matrix could be defined as a model for the structure. In this way, the new matrix $\mathbf{P}$ ($\tilde{\mathrm{P}}$ reduced) is called the PCA model. Geometrically, the transformed data matrix **T** (score matrix) represents the projection of the original data over the direction of the principal components **P**:

$$\mathbf{T} = \mathbf{XP}. \tag{3}$$

1.4 Damage detection indices based on PCA

Several damage detection indices based on PCA has been proposed and applied with excellent results in pattern recognition applications. In particular, two damage indices are commonly used: *Q*-index (or square prediction error SPE-index) and the Hotelling's T^2 statistic (or *D*-statistic). The first one is based on analyzing the residual data matrix **X** to represent the variability of the data projection in the residual subspace [17]. The second index is based on analyzing the score matrix **T** to check the variability of the projected data in the new space of the principal components.
The *Q*-index and the T^2 statistic can be calculated according to equations (4) and (5), respectively:

$$Q_i = e_i e_i^T = x_i(I - PP^T)x_i^T. \tag{4}$$

$$T_i^2 = \sum_{j=1}^{r} \frac{t_{sij}^2}{\lambda_j} = t_{si}\,\Lambda^{-1}\,t_{si}^T = x_i\,\mathbf{P}\Lambda^{-1}\mathbf{P}^{\mathbf{T}}\,x_i^T \quad (5)$$

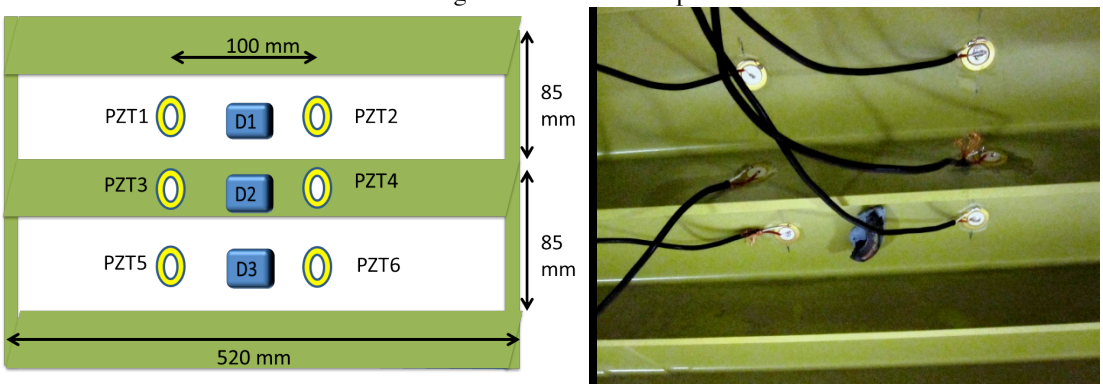
More details about these indices can be found in [17].

2. EXPERIMENTAL SETUP

The experimental setup consists of an aircraft skin panel instrumented with a piezoelectric system that works in several actuation phases. This skin panel is divided in small sections by means of stringers and ribs as shown in Figure 1. For testing the approach, two sections of this structure were used. The dimensions of each section and the damage description are depicted in Figure 2. These sections were instrumented with 6 PZT transducers as in Figure 2b. As excitation input, a BURST signal with 205 KHz as central frequency and nine peaks was used. Four different states of the structure were analyzed: the healthy structure and the structure with three different damages. Damages were simulated by adding a mass at three different positions (Figure 2), two of them on the skin and the other on the stringer. 100 experiments were performed and recorded: 25 with the undamaged structure and 25 more per damage. The aim of this artificial damage is to introduce reversible changes in the structure. To ensure a good signal to noise ratio each signal was averaged 10 times.



Figure 1. Aircraft skin panel



(a) (b)

Figure 2. Damage description and placement.

3. METHODOLOGY AND RESULTS

The developed methodology consists of two steps. First, a training step is developed by using data from the healthy structure and after the testing step is applied to the data from the structure in an unknown state. In both steps, the data from the structure are collected and organized in a unfolded matrix [12] which contains the information of the signal collected by the sensors in different parts of the structure by each actuation phase. To apply the methodology, as a preliminary step, normalization is applied to each matrix in both steps. Previous works by the authors [12][16] have shown that group scaling presents a better performance compared with other kind of normalizations,

because it considers changes between sensors and does not process them independently. More information about the normalizations can be found in [11],[12].

3.1 Training step

This step only considers the feature vector from the healthy state of the structure. To perform the training of the healthy state, first it is necessary to select a number $\boldsymbol{k}$ of random experiments from the healthy data set. These experiments are divided and grouped in training antibodies (AB_train) and antigens (AG_train). It is worth noting that the experiments used in both groups need to be different to include diversity in the system. Once these groups are defined, a comparison between the antibody set training and the antigen set training is performed. This comparison is applied by evaluating the affinity between both data sets. The affinity between AB_train and AG_train is defined in the same way as in [13] by the expression in equation (12). Note that both AB_train and AG_train are $n \times N$ matrices with n rows or experiments and N features.

$$aff(AB_train_i, AG_train_j) = 1 - \frac{1}{2} d(AB_train_i - AG_train_j) \tag{6}$$

where **aff** corresponds to the affinity and $\boldsymbol{d}$ to the Euclidean distance between the two data sets (AB_train and AG_train) which is defined by each vector of the matrix as follow:

$$d(AB_train_i, AG_train_j) = \sqrt{\sum_{k=1}^{N} (AB_train_{ik} - AG_train_{jk})^2} \tag{7}$$

Depending on the affinity value obtained in the previous step, the antibody must evolve and a new set of antibody is obtained as a result. This evolution consists on the mutation of the antibody and it is performed as in [13]. After that, this new set of data that is product from this evolution is again compared with the antigen training data set by means of the affinity. If this affinity value is larger than or equal to an affinity threshold T_h, then the antibody initializes the set of memory cell with the healthy state (MCH_SET) in other case it is eliminated. This dataset is saved in the memory of the AIS algorithm and corresponds to the learning step.

3.2 Testing step

The damage detection process is depicted in Figure 3. This process is based on the affinity value between the memory cell with the healthy state (MCH_SET) which act as an antibody, and the unknown data state that act as an antigen (data test). When the affinity is greater than or equal to the affinity threshold (T_h), the result is a healthy state. Otherwise, the result is defined as a damage state.

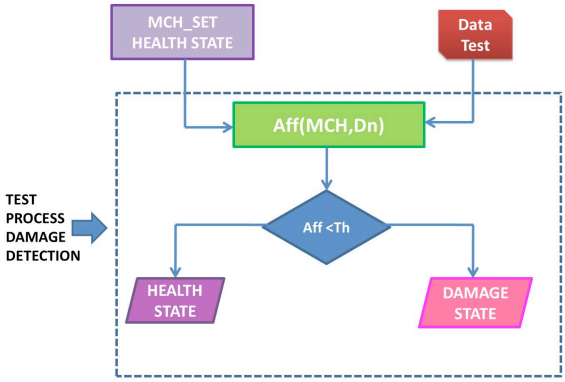


Figure 3. Damage detection process.

3.3. Results

The methodology it was applied to the data from all the actuation phases and the results from two of these phases are presented in Figures 4 and 5 (actuation phases 1 and 2), as it is shown, four

structural states are clearly distinguishable by using the affinity measurement. In each figure, the first 25 experiments correspond to the healthy state or baseline.

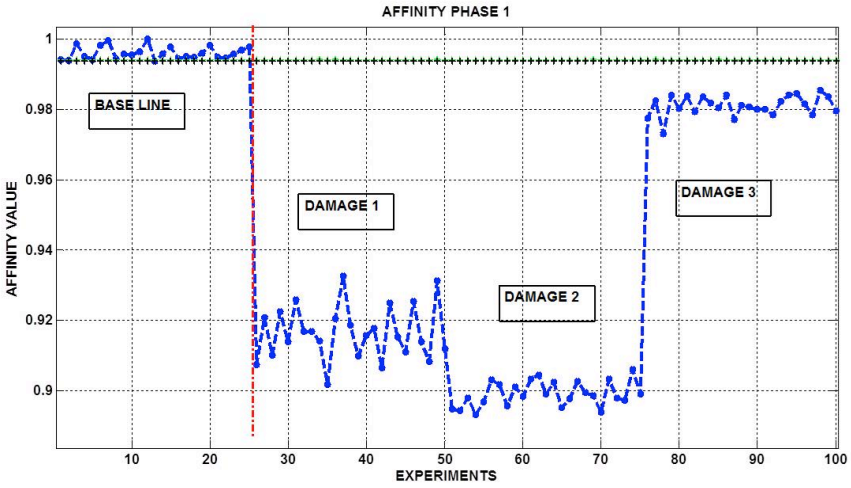


Figure 4. Affinity values in actuation phase 1.

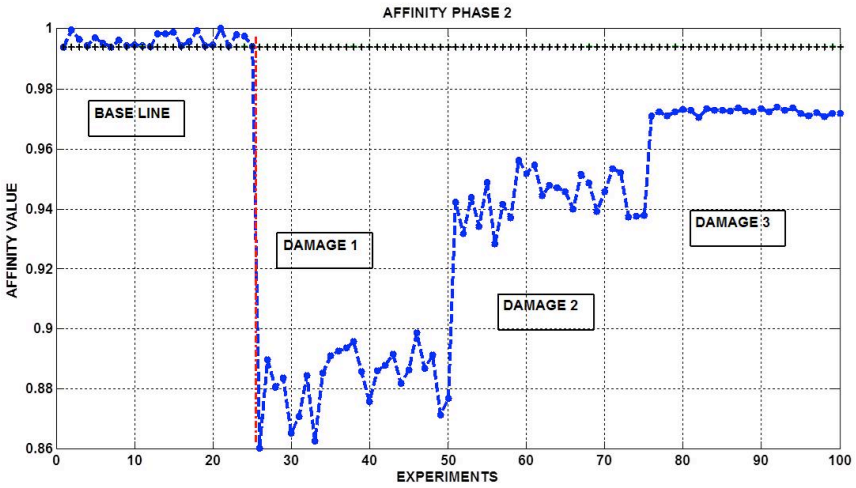


Figure 5. Affinity values in actuation phase 2

The first 25 experiments can be classified as a healthy state since they present a large affinity value (near to one) and, as it is expected, these affinities are greater than or equal to T_h. Contrarily, the affinity value from the rest of experiments is less than T_h, thus proving the presence of damage or abnormalities in the structure. In addition, it can be observed from these figures that each structural damage state is different from the others because their range of affinity presents different values. This result is useful for a future work and demonstrates that the methodology can also be used for damage classification.

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CONCLUSION

A new methodology for damage detection using artificial immune systems it was presented with excellent results. This methodology uses encoding to data-driven the information from the structure in different states and defines the presence of damages using a measure of affinity between the memory data set and the data from the structure under test. This methodology is able to detect damages, in all the cases, and independently of the actuation phase analyzed. Besides, the use of a threshold allows guaranteeing the results in the detection avoiding confusions in the interpretation of the results. In spite of the fact that the damages used in this paper are not fully realistic, these damages allow to test the methodology with reversible changes. However, the authors consider that other kind of damages can be easily detected by the proposed methodology since the it allows detecting structural changes by comparison with data that come from the pristine structure.

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