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Structural Health Monitoring using Artificial Immune System

Monitoramento estrutural da saúde usando sistema imunológico artificial

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ABSTRACT

This work proposes intelligent computer techniques which aims to detect structural damages in aircraft using the artificial immune system technique with negative selection and clonal selection. This concept results in a diagnosis system that is able to learn continuously, comprising different damage situations, without needing to restart the learning process. Considering this, two artificial immune systems were employed, the first of which, the negative selection algorithm, is responsible for pattern recognition, and second one, the clonal selection algorithm, is responsible for the continuous learning process. The experiment was prepared using piezoelectric transducers attached to an aluminum plate (representing an airplane wing), which act both as sensors and actuators, and signals that represent baseline and damage conditions were acquired. The results show that the proposed methodology is robust and accurate.

Keywords: Structural health monitoring, Isotropic structures, Artificial immune systems, Negative selection algorithm, Clonal selection algorithm.

RESUMO

Este trabalho propõe técnicas computacionais inteligentes que visam detectar danos estruturais em aeronaves utilizando a técnica do sistema imunológico artificial com seleção negativa e seleção clonal. Esse conceito resulta em um sistema de diagnóstico capaz de aprender continuamente, compreendendo diferentes situações de danos, sem a necessidade de reiniciar o processo de aprendizado. Considerando isso, dois sistemas imunológicos artificiais foram empregados, o primeiro deles, o algoritmo de seleção negativa, responsável pelo reconhecimento de padrões e o segundo, o algoritmo de seleção clonal, responsável pelo processo de aprendizado contínuo. O experimento foi preparado usando transdutores piezoelétricos conectados a uma placa de alumínio (representando uma asa de avião), que atuam como sensores e atuadores, e foram adquiridos sinais que representam as condições de linha de base e danos. Os resultados mostram que a metodologia proposta é robusta e precisa.

Palavras-chave: Monitoramento estrutural da saúde, Estruturas isotrópicas, Sistemas imunes artificiais, Algoritmo de seleção negativa, Algoritmo de seleção clonal.

1 INTRODUCTION

Ground, air, marine and space vehicles are everywhere. The presence of damages in these systems may compromise their safety, which might prevent them from operating. Structural failures have the potential of causing financial losses and, in the worst-case scenario, they may affect lives (ZHONGQING SU et al., 2009). These failures result from structural damages which attained a critical level, thus leading to the collapse of the structures.

Structural health monitoring (SHM) detects damages at their early stages, intervening on their propagation, and preventing full stop or structural damage from happening (HALL, 1999).

According to Doeblings et al. (1998), SHM can be classified based on levels of comprehensiveness:

- Level 1 – Detects the presence of damages;
- Level 2 – Detects and indicates the location of damages
- Level 3 – Detects, locates and quantifies the damages;
- Level 4 – Detects, locates, quantifies the damages, and then estimates the remaining useful life of the system.

Inman (2001) added three more levels, comprising the use of intelligent materials:

• Level 5 – Combines level 4 with intelligent structures for auto diagnosing structural damages;

• Level 6 – Combines level 4 with intelligent structures and control to obtain an auto repairing system

• Level 7 – Combines level 4 with active control and intelligent structures for obtaining a system of control and monitoring simultaneously.

Louzada (2013) further added that there are four stages for implementing an SHM system:

1- Signal acquisition or transmission from the structure to be monitored, using sensors, actuators, types of mesh, etc;

2- Since the data obtained are raw, it is necessary to analyze them through filters, normalization techniques, among others, so that a better interpretation of these data can be obtained;

3- Damage diagnosis is carried out, that is, verifying whether the system presents damages or not;

In the last stage, nondestructive techniques, intelligent systems, among others, are applied to generate the final output of the system.

The technique for monitoring a structure depends on the constructive configuration, the testing environment and the type of structure, which can be based on nondestructive techniques (NDT). For instance: wave propagation (Lamb waves) (GONSALES, 2012).

After the signal is acquired, it is possible to use artificial intelligence systems for signal processing, can determine whether damages are present in the structure or not, their locations and severity (FRANCO et al., 2009).

According to Lopes et al. (2000), artificial neural networks (ANN) emerged as a tool for monitoring and classifying machines and equipment. They solve problems of damage detection and monitoring due to their pattern recognition and interpolation characteristics.

Morales (2009) applied three architectures of the genetic algorithm for detecting damages in beams, trusses and frames considering different damage conditions. The methodology presented a good behavior for damage detection, but when the measurements were full and free of noise. For incomplete measurements, the author proposes using the expansion technique.

Lima (2014) used the Artificial Immune Systems (AIS) and artificial neural networks for monitoring the health of mechanical structures, presenting satisfactory results and demonstrating the efficiency of the techniques applied.

Souza et al. (2015) presented a comparative study using the following algorithms: K-Means, Fuzzy C-Means and the Kohonen Artificial Neural Network, when monitoring the structural health of an agricultural tractor. Such techniques classified the data based on the similarity between clusters. To assess the algorithms, the modeling and simulation signals were carried out based on a numerical model of the agricultural tractor.

Lima et. al (2018) presented a hybrid algorithm based on artificial neural networks and the wavelet transform for monitoring the structural health of aeronautic structures.

The works mentioned above used intelligent systems to enable the acquisition of knowledge and information from complex processes, and, therefore, analyze their signals, thus providing automated decision-making.

This work proposes for developing SHM based on intelligent computer techniques with the purpose of detecting damages in an aircraft structure using artificial immune systems, such as the negative and clonal selection algorithms.

The use of the Negative Selection Algorithm (ASN) and Clonal Selection (CLONALG) is due to their pattern recognition and continuous learning characteristics, as well as to the fact that they presented a good results in other problems involving pattern recognition and diagnosis, as highlighted by Lima (2016).

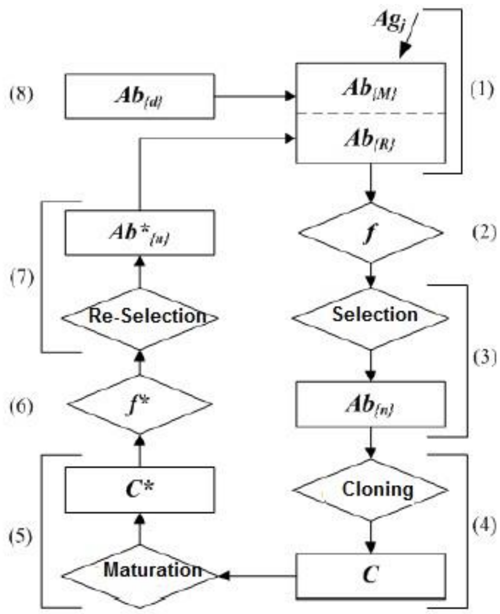
The functioning of the negative selection algorithm can be verified in the work of (Oliveira et. al (2019).

2 CLONAL SELECTION (CLONALG)

The clonal selection algorithm (CLONALG) was proposed by De Castro and Zuben (2000). In this algorithm, two characteristics of the clonal selection principle are considered: (1) maturation and (2) selection proportional to the affinity. There are two versions of such algorithm in the literature: the first one for problems involving machine learning and pattern recognition, and the second one for optimization problems (DE CASTRO, 2001).

The CLONALG algorithm for problems involving pattern recognition and machine learning is illustrated in Figure 1.

Figure 1 – Flowchart of the CLONALG.



Source: Adapted from Lima (2016).

The CLONALG algorithm can be described according to the steps presented below (DE CASTRO, 2001; DE CASTRO, TIMMIS, 2002):

Step I: Initialization: randomly generate a population (Ab=Ab_M+ Ab_R) with n lymphocytes for each antigen (Ag_i). N is given by $M+R$;

Step II: Affinity evaluation: each antigen (Ag_i) is presented to the lymphocytes of the population (Ab) in the process of affinity evaluation. An affinity vector f is determined;

Step III: Selection: the n lymphocytes with the highest values of affinity f in relation to (Ag_i) are selected to compose the subpopulation (Ab_n);

Step IV: Cloning: the n lymphocytes selected (cloning) proliferate proportionally to the affinities of the antigen (Ag_i), generating a population C of clones. The higher the affinity f is, the higher the number of selected lymphocytes n is;

Step V: Hypermutation: afterwards, the population C of clones is subjected to a process of affinity maturation, generating a new population C^*, where each lymphocyte undergoes mutation at a rate that is inversely proportional to the affinity f;

Step VI: Affinity evaluation: determine the affinity f^* between the mutated set C^* of clones and the antigen (Ag_i);

Step VII: Re-selection: from the mature population C*, re-select the n best maturated lymphocytes composing the subpopulation (Ab_n). From this subpopulation, the best lymphocytes are selected to compose the memory set (Ab_M). The lymphocyte composes the memory set when it presents high affinity rates, and may replace a memory lymphocyte;

Step VIII: Metadynamics: replace d antibodies of (Ab_R) for (Ab_d) new individuals, thus inducing diversity in the repertoire. The antibodies with the lowest affinities are selected to be replaced;

Step IX: Repeat steps II through VIII until a stopping criterion is met.

At the end of the iterative process, the memory set (Ab_M) presents M lymphocytes with high affinity rates in relation to the antigen (Ag_i). This memory set is used by the NSA for detecting and classifying the antigen that was learned in the process of clonal selection.

It is worth mentioning that for learning problems, step VIII (metadynamics) is not carried out; therefore, d = 0. The number Nc of clones generated in Step IV for each lymphocyte i is given by equation 1 (DE CASTRO, 2001):

$$Nic = round(BN / i) \tag{1}$$

Where:

β: multiplying factor between [0,1];

N : total number of lymphocytes of the population Ab;

round : operator which rounds the value to its closest integer;

The mutation rate (α) of each clone is defined by equation 2 (DE CASTRO, 2001):

$$a = \exp(-pfn) \tag{2}$$

Where:

p: control parameter of the decay of the exponential function;

fn: normalized value of the affinity f;

The normalized value of the affinity f can be calculated as presented by equation 3:

$$fn = (f / f\max) \tag{3}$$

Where:

f : affinity value;

fmax : maximum affinity value;

Therefore, each clone undergoes a mutation process given by (DE FRANÇA et. al, 2005):

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$$m = round(a * N(0,1)) \tag{4}$$

Where:

m: number of mutations;

round : operator which rounds the value to its closest integer;

α: mutation rate;

N: random gaussian variable whose mean is equal to zero and standard deviation equal to one.

In this work, the modules were divided in: data acquisition module composed by the experimental set-up obtained by (ROSA, 2016), censoring module, novelty detection module, continuous learning module, monitoring module of the NSA, and knowledge update module.

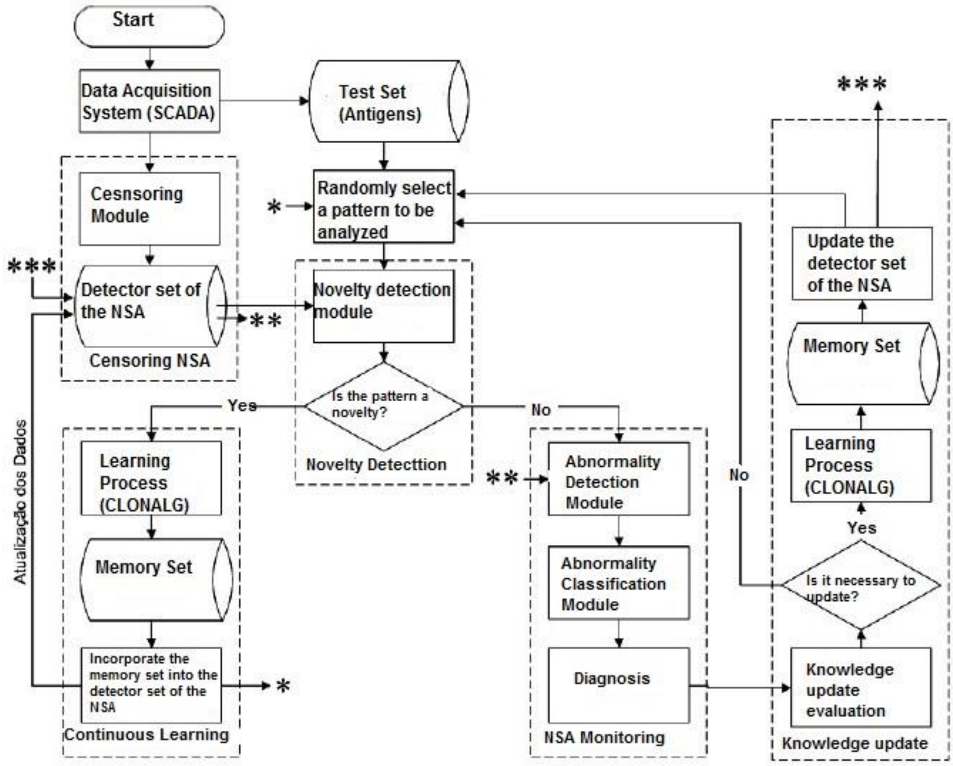
3 MATERIAL AND METHODS

The experimental measurements of the aluminum plate obtained by (Rosa, 2016) were used, which, in turn, were manipulated by (Oliveira, 2017), and subjected to the methodology of the artificial immune systems, such as: the negative selection algorithm and clonal selection.

The SHM system was composed of six main modules: data acquisition system, censoring module of the SHM, novelty detection module, continuous learning module, monitoring module of the NSA, and knowledge update module.

Figure 2 depicts the use of the NSA for damage detection and location, and CLONALG for the continuous learning strategy.

Figure 2 – Flowchart of the algorithm with continuous learning.



Source: Adapted from Lima (2016).

Data acquisition system: the data were obtained by (Rosa, 2016) and manipulated by (Oliveira, 2017). The data were used in the following modules: censoring of the NSA, novelty detection, continuous learning, monitoring of the NSA, and knowledge update.

Censoring module of the NSA: the diagnosis system was carried out in two stages, online and offline. In the offline process, the initial learning of the system was carried out (training), which is called censoring module. In this process, the self detectors were defined, composing the detector set of the NSA. This set of self detectors is regarded as the knowledge of the intelligent system for decision-making during the online process. The detectors was composed of 81 points of the signals which present the normal condition of the structure, and 405 points of the signals which present characteristics of the damages, that is, the many different damage situations.

In this context, the set of self detectors was generated by randomly choosing between normal signals and signals with non repeating damages in the dataset. The data were compared pointwise with the self detectors. If a match occurred, the random vector was rejected, because self characteristics were identified. Otherwise, it was accepted and then stored as a self detector into the self detectors set.

Once the self detectors set was obtained, it was used in the stages of the diagnosis system, such as: novelty detection, continuous learning module, monitoring module of the NSA and knowledge update module. After carrying out the process offline, the monitoring process was carried out online.

Novelty detection module: in the process of online monitoring of the system, the antigen set was obtained. This set was composed of the signals from the dataset. Afterwards, a signal was randomly chosen for analysis. This signal was then subjected to the novelty detection module. In the novelty detection stage, a comparison between the signal under analysis and the detector set of the NSA was performed. If a match occurred, such a signal was considered as already known by the system, that is, it was not a novelty. Otherwise, it was considered as a novelty, that is, unknown by the system.

When the system identified a novelty, the continuous learning stage was activated with the purpose of learning about the new antigen (signal under analysis), which is characterized as the continuous learning process by the CLONALG algorithm. When the signal was known by the system, it was analyzed by the monitoring module of the NSA, which is described below.

Continuous learning module: the CLONALG algorithm aimed to generate a memory set (knowledge) from the unknown signal (antigen). Firstly, a population of lymphocytes was randomly generated. To quantify the affinity between the lymphocytes of the population (Ab). Afterwards, the N best lymphocytes with the highest affinity values in relation to the antigen were selected for the cloning and hypermutation processes. The number of clones was calculated by equation 1 and the number of mutations was determined by equations 2 and 4. The purpose of mutation was to perform slight modifications in the structure of the lymphocytes, thus increasing the affinity in relation to the antigen.

In this methodology, as the signals analyzed were expressed as vectors with positive and negative real numbers, it was necessary to use an inductive technique (WYLIE; SHAKHNOVICH, 2012).

After carrying out the maturation of the lymphocytes, the N best maturated clones were re-selected to be incorporated into the population again. The selected lymphocytes replaced the worst ones of the population. Afterwards, the best lymphocytes of the population were set aside for the memory set. The process was repeated until a stopping criterion was met. In this research, the stopping criterion was determined by the number of iterations.

After completing the learning process, a memory set (knowledge) in relation to the unknown antigen was obtained. This knowledge set was incorporated into the detector set of the NSA, thus providing knowledge to the system, so that for future analyses that involve the same antigen the system is able to recognize and classify the damage. Such process was defined as continuous learning.

Knowledge update module: after carrying out the continuous learning process and obtaining the memory set, the detector set of the NSA was updated.

Monitoring module of the NSA: when, in the novelty detection stage, a novelty was not identified, that is, the antigen was already known by the NSA and the signal under analysis was compared to the detector set of the NSA and both affinity and match were evaluated, it was possible to detect the signal containing damage and then classify it according to the many different damage situations. Afterwards, the monitoring process of the NSA was then completed.

For the immune system algorithm to work well, considering continuous learning, some parameters of the NSA and CLONALG were used. After empirical tests, the parameters which presented the best performance for the system are listed in table 1. The affinity rate was defined to be equal to 30% due to the fact that the characteristics of the signals were similar.

Table 1 – Parameters.

Parameters	NSA without continuous learning	NSA with continuous learning
N	-	20
n	-	4
β	-	0.3
d	-	0
deviation	0.3	0.3
affinity	30%	30%
roh	-	3

Source: Elaborated by the authors.

4 RESULTS AND DISCUSSION

The proposed methodology was evaluated by assessing the efficiency, accuracy and robustness in the process of structural health monitoring using the conventional algorithm (without continuous learning) and the algorithm with continuous learning.

With the purpose of assessing the performance of the modules of novelty detection, continuous learning and knowledge update in the algorithm proposed in this work, the censoring phase in both systems (without and with continuous learning) was carried out excluding a pattern, which in this case was the damage number 5, and thus the algorithm began the online monitoring process without a previous knowledge about the patterns.

After applying the negative selection algorithm to the test set of the five damage situations, the results presented in Table 2 were obtained.

Table 2 – Results for the conventional algorithm – 4 situations with damage and 1 without damage.

Patterns	Tested Patterns	Correct Patterns	Score of accuracy (%)
Baseline	81	68	83,95
Damage 1	81	81	100,00
Damage 2	81	81	100,00
Damage 3	81	81	100,00
Damage 4	81	81	100,00
Damage 5	0	0	0
Total	405	392	96,79

Source: Elaborated by the authors.

Based on table 2, the negative selection algorithm could not identify the pattern that was excluded from the censoring process, that is, without a previous knowledge of the damage. Therefore, the SHM could not identify damage number 5, and the score of accuracy was equal to zero. The structural health analysis system carried out for the isotropic material presented a score of accuracy equal to 100,00% for the best configuration, and that the number of detectors influenced directly on the recognition of damages.

Table 3 presents the results obtained by the structural health monitoring with continuous learning for the same condition as Table 2.

Table 3 – Results of the algorithm with continuous learning – 4 situations with damage and 1 without damage.

Patterns	Tested Patterns	Correct Patterns	Score of accuracy (%)
Baseline	81	81	100,00
Damage 1	81	81	100,00
Damage 2	81	81	100,00

Damage 3	81	81	100,00
Damage 4	81	81	100,00
Damage 5	81	81	100,00
Total	486	486	100,00

Source: Elaborated by the authors.

Given the results from Table 3, it is possible to observe that the system with continuous learning was able to learn the unknown damage and, based on this, could diagnose the damage in the next analysis. Also, it is possible to observe that the knowledge update module contributed to the NSA such that the score of accuracy for the baseline attained 100%, even considering that the system already had a previous knowledge about this pattern. This is due to the fact that the SHM updates the detector set of the NSA in the online monitoring process, thus providing a reinforcement and improvements to the knowledge.

Another test was carried out excluding two patterns, which in this case were damages number 1 and 3, and then the algorithm began the process of online monitoring without a previous knowledge of such patterns.

When the negative selection algorithm was applied to the test set of the five damage situations, the results presented in Table 4 were obtained.

Table 4 – Results for the conventional algorithm – 3 situations with damage and 1 without damage.

Patterns	Tested Patterns	Correct Patterns	Score of accuracy (%)
Baseline	81	81	100,00
Damage 1	0	0	0
Damage 2	81	81	100,00
Damage 3	81	81	100,00
Damage 4	81	81	100,00
Damage 5	0	0	0
Total	324	311	63,99

Source: Elaborated by the authors.

Based on Table 4, it is possible to observe that the negative selection algorithm could not identify the patterns excluded from the censoring process, that is, without a previous knowledge about the damage. Therefore, the SHM could not identify damages number 1 and 3, and the scores of accuracies were equal to zero. The structural health analysis system for the isotropic material presented a score of accuracy equal to 100,00% for the best configuration, as well as that the number of detectors influences directly on the recognition of the damages.

Table 5 presents the results obtained by the structural health monitoring system with continuous learning for the same condition as Table 4.

Table 5 – Results of the algorithm with continuous learning – 3 situations with damage and 1 without damage.

Patterns	Tested Patterns	Correct Patterns	Score of accuracy (%)
Baseline	81	81	100,00
Damage 1	81	81	100,00
Damage 2	81	81	100,00
Damage 3	81	81	100,00
Damage 4	81	81	100,00
Damage 5	81	81	100,00
Total	486	486	100,00

Source: Elaborated by the authors.

Comparing tables 4 and 5, it is possible to observe that the negative selection algorithm did not recognize the patterns excluded from the censoring process, which leads to a score of accuracy equal to 0%. Afterwards, the system with continuous learning was used and the patterns were recognized, which led to a score of accuracy equal to 100,00% for the five different damage situations.

5 CONCLUSION

In this work a structural health monitoring system was developed, and it could detect and locate damages in an aeronautical structure using artificial immune systems with the negative selection and clonal selection algorithms.

For the NSA, it was possible to verify, based on the tests carried out, that the higher the knowledge obtained in the censoring module, the higher the efficiency in the recognition process and classification of the algorithm in the monitoring module.

Based on the tests carried out, it was possible to verify that the continuous learning learns about the unknown damage, thus enhancing the results for the next analysis, as well as that the cross-validation test provides reliability and speed.

The knowledge update module contributed to the continuous learning, which led to an increase in the scores of accuracies, and this is due to the fact that the detectors set in the

NSA is updated in the online monitoring process, thus providing robustness and improvements to the knowledge.

Therefore, we conclude that the algorithm proposed in this work, which is based on intelligent computer techniques, was efficient, reliable, robust and accurate for the process of structural health monitoring in isotropic structures, and that this work contributes to the research field of SHM.

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