Structural failures diagnosis using a hybrid artificial intelligence method

Diagnóstico de falhas estruturais utilizando um método híbrido de inteligência artificial

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ABSTRACT
This paper presents a Wavelet-artificial immune system algorithm to diagnose failures in aeronautical structures. Basically, after obtaining the vibration signals in the structure, is used the wavelet module for transformed the signals into the wavelet domain. Afterward, a negative selection artificial immune system realizes the diagnosis, identifying and classifying the failures. The main application of this methodology is the auxiliary structures inspection process in order to identify and characterize the flaws, as well as perform the decisions aiming at avoiding accidents or disasters. In order to evaluate this methodology, we carried out the modeling and simulation of signals from a numerical model of an aluminum beam, representing an aircraft structure such as a wing. The results demonstrate the robustness and accuracy methodology.

Keywords: Wavelet Artificial Immune Systems (WAIS), Monitoring and Fault Identification, Aeronautical Structures, Artificial Intelligence.

RESUMO

Este artigo apresenta um algoritmo do sistema imunitário Wavelet-artificial para diagnosticar falhas em estruturas aeronáuticas. Basicamente, após a obtenção dos sinais de vibração na estrutura, é utilizado o módulo wavelet para transformar os sinais no domínio wavelet. Posteriormente, um sistema imunitário artificial de selecção negativa realiza o diagnóstico, identificando e classificando as falhas. A principal aplicação desta metodologia é o processo de inspecção de estruturas auxiliares, a fim de identificar e caracterizar as falhas, bem como executar as decisões destinadas a evitar acidentes ou desastres. Para avaliar esta metodologia, realizámos a modelação e simulação de sinais de um modelo numérico de uma viga de alumínio, representando uma estrutura de aeronave, como uma asa. Os resultados demonstram a robustez e a metodologia da precisão.

Palavras-chave: Sistemas Imunitários Artificiais Wavelet (WAIS), Monitorização e Identificação de Falhas, Estruturas Aeronáuticas, Inteligência Artificial.

1 INTRODUCTION

In recent years the aeronautical industries, started applying many investments in research and technological development in order to obtain efficient methods to analyze the integrity of structures and to prevent disasters and/or accidents from happening, ensuring people's lives and avoid economic damages.

Fault diagnosis systems, or as better known, "Structural Health Monitoring (SHM) system" perform tasks such as: acquisition and data processing, validation and analysis, detection, characterization and interpretation of adverse changes in a structure so to assist taking decisions and identify structural faults [1].

Structural failures occur as a consequence of factors such as component wear, cracks, loosening of screw connections, or simply the combination of these. The flaws in most cases, not dependent on the source or current, causes a variation of spatial parameters of the structure, generating a reduced structural rigidity, mass, and also the increased damping so that the dynamic behavior of the structure is changed [2].

To solve this problem, several solutions have been proposed, such as traditional SHMS based on ultrasonic inspection, radiography (X-ray), acoustic emission testing, among others. However, these traditional techniques cannot meet increasing demands of industries, especially when the structures are in motion [3]. Thus, a solution to develop the most modern and efficient SHMs is the utilization of intelligent techniques, and efficient data acquisition systems.

In the literature, several studies that utilize smart materials and SHM systems are available, which have robustness, accuracy and good performance. Following presents the most relevant papers.

In [4], the authors presented the application of a genetic algorithm in conjunction with a Perceptron Multi-Layer neural network with backpropagation to perform fault detection and location in a numerical model of a beam. In [5] is used the method of electro-mechanical impedance to monitor aerospace structures with assets piezoelectric sensors attached. Reference [6] presents a methodology for structural analysis of buildings using a non-destructive method (NDT). In [7] is propose a fuzzy system to detect structural faults using curvature mode shapes.

In the work [8] proposed a model using wavelet transform to evaluate integrity of bridge structures through the vibration signals. A system for the identification and location of damage to an airplane wing using a probabilistic neural network was proposed in [9]. In [10] proposed a multimodal genetic algorithm for diagnosing damage in a steel truss bridge. In [11] the authors propose an experimental method for performing structural analysis of buildings. In [12] proposes an ARTMAP-Fuzzy neural network applied in the diagnosis of faults in buildings. Already in [13] proposed an immune algorithm with negative selection to diagnose failures in aircraft structures.

Reference [14] was shown a SHM based on ARTMAP-Fuzzy neural network and wavelet transform to diagnose faults in buildings. In [15] a hybrid method based on ARTMAP-Fuzzy neural network and wavelet transform to diagnose failures in aluminum beams was presented. Reference [16] presented a failure analysis tool in aircraft structures using complex wavelet transform. The paper [30] proposes intelligent computer techniques which aims to detect structural damages in aircraft using the artificial immune system technique with negative selection and clonal selection.

In this paper, presents a new approach to fault diagnosis in aeronautical structures using a Wavelet-artificial immune system algorithm. This methodology is divided into three main modules, with the acquisition and processing of data, fault detection and classification. From the acquisition of the signs applies to wavelet transform, decomposing the signs at four levels of resolution. After you obtain the processed signals via the wavelet transform, applies to Negative Selection Algorithm to perform the detection of abnormalities in the structure, and the characterization of structural faults detected.

The artificial immune systems (AIS) are promising algorithms in Artificial Intelligence (AI); the concept is based on biological immune systems (BIS) and aims to computationally reproduce its principal characteristics, properties and abilities [7], [31]. As emphasized in [18], the AIS are adequate tools to be applied in failure diagnosis due to the natural characteristics of diagnoses. These characteristics are related to biological inspiration. The AIS was inspired in the biological immune system, which have natural characteristics of diagnosing of disease in the human organism.

The wavelet transform is a mathematical tool for signals analysis through decomposition or breakage of the constituent parts, allowing to analyze the data in different levels of frequency with the resolution of each component in its range. In summary the wavelet transform allows you to view the approximation of the discontinuous data in functions, that is, view the abnormalities in the signals, so becomes an important tool in the analysis and diagnosis of abnormality in the aeronautical structures. The use of a wavelet transform provides, to the diagnosis system, a sensitivity that allows the system to easily identify abnormalities in the signals.

Several studies are presented in the literature, however, the great advantage of the method presented in this Work is the ability to filter the signals using wavelet module, and thereafter applying the negative selection algorithm, which is one of the most efficient techniques for failure diagnosis. This combination generates a powerful failure analysis tool, and the results obtained demonstrate it.

Thus, in this work the main contribution is a new hybrid approach using a mathematical tool for signal processing and an intelligent method, which together provide efficiency and accuracy to failure diagnosis.

In order to evaluate the proposed methodology, we used one database containing the signals numerically simulated from a model of an aluminum beam, that represents the wing of aircraft. This structure was modeled by finite elements and simulated in MATLAB. The results demonstrate the efficiency, accuracy and robustness of the proposed method.

This text is organized as follows: Section 2 presents the negative selection algorithm. Section 3 describes the wavelet transform. The modelling and simulation is presented in section 4. Section 5 presents the proposed methodology. Finally, the results and conclusions are presented, respectively, in sections 6 and 7.

2 NEGATIVE SELECTION ALGORITHM (NSA)

The NSA, which was proposed in [19] to detect changes in systems, is based on the negative selection of T lymphocytes over time. This process works on the discrimination of proper vs. non-proper cells. The algorithm is executed in two phases, according to the following description [17, 20]:

1. Censor

a) Define a set of proper chains (*S*) to be protected;

b) Generate random chains and evaluate the affinity (Match) between each chain and the proper chains. If the affinity is greater than a predefined value, then reject the chain. Otherwise, file the chain into a detector set (*R*).

2. Monitor

a) Given a set of chains to be protected (protected chains), evaluate the affinity with each chain and the detector set. If the affinity is superior to a predefined value, then a non-proper element is identified.

The censor-phase of the NSA primarily consists of generating a detector set from the data that were randomly chosen and verifying which data can recognize a non-proper pattern. The detectors are similar to mature T cells, which can recognize pathogenic agents [21].

The monitoring phase consists of monitoring a system to identify a change in the behavior; thus, this phase classifies the change using the detector set that was created in the censor-phase. The censor-phase occurs offline, and the monitoring-phase occurs in real time [17, 21].

The antigen (*Ag*) is the signal to be analyzed in the negative selection algorithm and can be represented by expression (1). The detectors represent the antibodies (*Ab*) and are expressed according to expression (2) [18, 20]:

$$Ag = Ag_1, Ag_2, Ag_3, Ag_4, \ldots, Ag_L \quad (1)$$

$$Ab = Ab_1, Ab_2, Ab_3, Ab_4, \ldots, Ab_L \quad (2)$$

where L is the dimension of the space of the antigen and the antibody.

2.1 MATCHING CRITERION

To evaluate the affinity with the chains and to prove that they are similar, the matching criterion is used, which has the same meaning as the combination. The matching can be perfect or partial [22].

The matching is perfect when the two analyzed chains have the same value in every position, and the matching is partial when the patterns have only one identical position value to confirm the matching, which is previously defined [18]. This quantity is known as the affinity rate. The affinity rate represents that there is a similar grade for matching to occur between two analyzed chains [20]. Reference [22] defines the affinity rate according to the following equation:

$$TAf = \left(\frac{An}{At}\right)*100 \qquad (3)$$

where:

TAf : affinity rate;

An : quantity of normal rates in the problem (proper rates);

At : total number of chains in the problem (proper and non-proper chains).

Equation (3) allows the precise calculation of the affinity rate for the proposed problem and represents the statistical analysis with the samples of the problem.

To dynamically improve the diagnosis, a deflection is proposed that is attached to the antibody (detector pattern - *Ab*), i.e., a tolerance with which it is possible to accept the combination with the patterns. This tolerance is defined according to equation (4) [18]. This deflection acts individually in each position *i* of vector (*Ab*), allowing verification of the matching in each position:

$$\underline{Ab}_i \leq Ag_i \leq \overline{Ab}_i \qquad (4)$$

where:

Ag_i : nominal value of position *i* of the antigen (pattern under analysis);

$\underline{Ab}_i$: nominal value of position *i* except for the deflection adopted at the antibody (detector pattern);

$\overline{Ab}_i$: nominal value of position *i* plus the deflection adopted at the antibody (detector pattern).

In this way, if the value of position *i* of antigen (*Ag*) is in the interval expressed in equation (4), then the position is considered to match. Thus, it is possible to quantify the affinity using the patterns, analyzing position-by-position (point-by-point).

Expression (5) represents the method for quantifying the total affinity with the analyzed patterns [23]:

$$Aft = \sum_{i=1}^{L} Pc_i \qquad (5)$$

where:

Af_T	:	% of the affinity with the patterns analyzed;
L	:	total quantity of positions;
Pc	:	matched position;
$\sum_{i=1}^{L} Pc$	:	sum (quantity) of the matched positions.

Thus, if *Aft* is greater than *TAf*, then the combination/matching with the patterns occurs, i.e., the patterns are considered to be equal/similar. Otherwise, there is no matching with the patterns.

3 WAVELET TRANSFORM

The wavelet functions are mathematical transforms that can decompose the functions, which allows these functions to be re-written in more detail, i.e., with a global vision. Thus, it is possible to differentiate the local characteristics of a signal with different sizes (resolutions) and to analyze all of the signals by translations. Because most of the wavelets have compact support, they are useful in analyzing non-stationary signals. In this way, the wavelet analysis is better than the Fourier analysis [24].

There are several wavelet families. This work considers the orthonormal family functions and the Daubechies discrete family [25] due to having faster computational algorithms [24].

3.1 DISCRETE WAVELET TRANSFORM (DWT)

Define a signal $y[t] = (y_0, \dots, y_{n-1}, y_n)$, which represents a discrete vector; then, it can be represented by a wavelet series, as follows [24]:

$$y[t] = \sum_{k=0}^{N_J} c_{J,k}\phi_{J,k}(t) + \sum_{j=J}^{1}\sum_{l=0}^{N_j} d_{j,k}\upsilon_{j,k}(t), \nabla t \in [0, N_0] \quad (1)$$

where J represents the resolution level, $N_j = (N/2) - 1$ represents the quantity of points in each new vector obtained by transformation; $\phi_{j,k}(t)$ and $\upsilon_{j,k}(t)$ are the wavelet and scale functions that perform the transformation; j is the scale (dilation); and k is the position (translation).

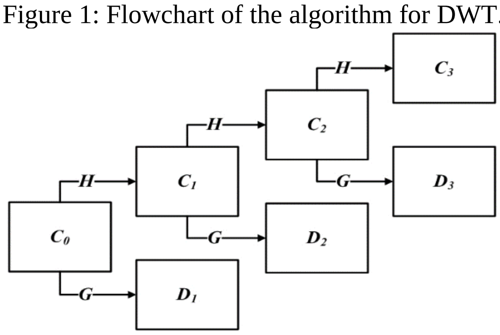
The discrete wavelet transform (DWT), when applied directly to a signal to generate a set of coefficients, is calculated by several entrances into a G filter (low pass) and H filter (high pass), which are known as resolution levels. The filters G and H are vectors that have constants that are already calculated and that provide an orthogonal base that is related to the scale and wavelet functions, respectively. This process is known as the Mallat Pyramidal algorithm [24] and is shown in Figure 1.

In Figure 1, C_0 corresponds to the original discrete signal ($C_0 = y[t]$), and H and G represent the low-pass and high-pass filters, respectively. The parameters d_1, d_2 and d_3 are the wavelet coefficients or the detail at each resolution level, and C_3 are the scale coefficients or approximations at the last level of the transform. These coefficients are obtained by a convolution of the constants with the filters (7) and (8) [24]:

$$C_{j+1,k} = \sum_{l=0}^{D-1} h_l C_{j,2k+l} \quad (6)$$

$$d_{j+1,k} = \sum_{l=0}^{D-1} g_l C_{j,2k+l} \quad (7)$$

Figure 1: Flowchart of the algorithm for DWT.



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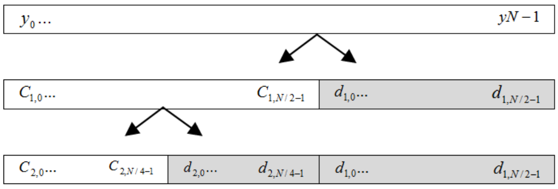
where $k = [0, \ldots, (N/2^j) - 1]$, and D is the number of constants in the filter. Thus, the coefficients $C_{j,k}$ represent the average local media, and the wavelet coefficients $d_{j,k}$ represent the complementary information or the details that depart from the average media. Therefore, the transform coefficients, when ordered by scale (*j*) and position (*k*), are represented as follows [24]:

$$\psi = \left((C_{J,k})_{k=0}^{N_J}, \left((d_{j,k})_{k=0}^{N_J} \right)_{j=J}^{1} \right) \quad (8)$$

such that ψ is a finite representation in terms of the coefficients of the signal decomposition in equation (6). Figure 2 shows the decomposition process of a signal at two resolution levels. Observe that at each transformation level, the size of the vectors is reduced by half ($N/2^J$). This figure represents an adaptation of the figure that represents the pyramidal algorithm for DWT.

Figure 2: Adaptation of the Pyramidal algorithm for DWT.



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4 MODELING AND SIMULATIONS

The aluminum beam model proposed to evaluate the methodology, obtained by finite element method, was an aluminum beam in the cantilever-free condition discretized with 10 finite elements with 2 degrees of liberty each. The material properties used are the modulus of elasticity (E = 700 GPa) and the density (γ = 2710 kg/m3). The dimensions are 500mm long, 25mm wide and 5mm thick. Figure 3 illustrates the patterned beam [26]. From the beam model were performed several simulations with different percentages of wear and locations of faults. The database consists generated signal captured by an accelerometer attached to the beam. In all simulations the beam was excited in the 3rd degree of freedom (finite element 2) and the signal was captured on the 19th degree of freedom (finite element 10). Thus, were simulated 1400 signals in the structure, 500 without wear (base-line condition) and 900 signs with wear (structural failure), such as presented in the table 1.

Figure 3: Aeronautical structure modeled.

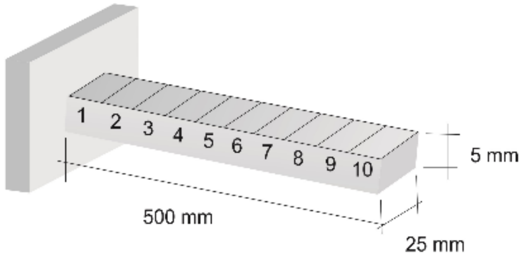

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Table 1: Number of signals simulated.

Wear level	Number of simulations
Normal condition (0%)	500
5%	150
10%	150
15%	150
20%	150
25%	150
30%	150
Total	1400

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To each type of failure were simulated 150 signals, and to the normal condition were simulated 500 signals.

5 PROPOSED METHODOLOGY

Neste trabalho, foi apresentada uma nova abordagem para o desenvolvimento de um sistema de reconhecimento

The WAIS proposed in this work to detect and classify failures is based on the negative selection principle, and the phases are presented as follows:

5.1 CENSOR-PHASE

This phase generates the proper detectors and the disturbance detector set. The detector sets are used by the diagnosis system during the monitoring process. The detectors are generated for each kind of signal in the database generated in the modeling and simulation.

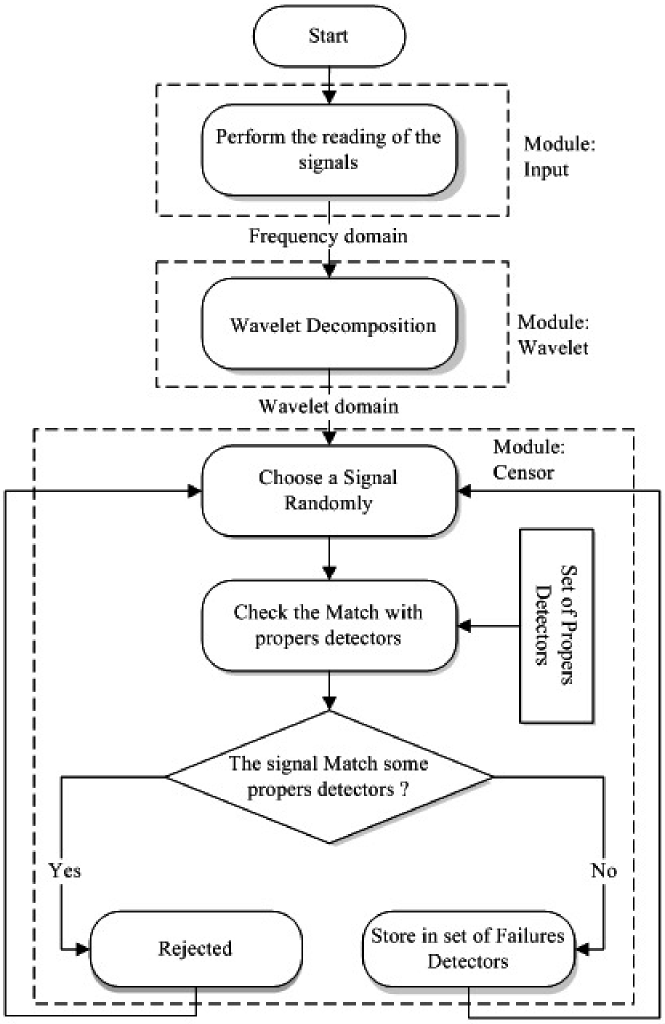
The proper detectors represent the normal condition of the structure (base-line). To generate this kind of detector, are selected randomly normal signals, and these signals are defined as proper detectors.

Once a proper detector is generated, it is possible to generate the failures detectors. This process is illustrated in Figure 4.

Next, the procedure is divided into three modules: the reading of the signals to create the detectors, the wavelet module that decomposes the signals using a discrete wavelet transform with four resolution levels, and the censor module with which the signals are randomly chosen and that verify the matching in relation to the proper detector set. If the affinity criterion is satisfied, the signals are rejected because they have proper characteristics. Otherwise, the signals are placed in the failure detector set.

The quantity of detectors that are used is determined by the operator. However, it is recommended to use 30% of the available data. The matching criterion is proposed in [27], which uses a deviate of 3%.

Figure 4: Flowchart of the censor-phase.



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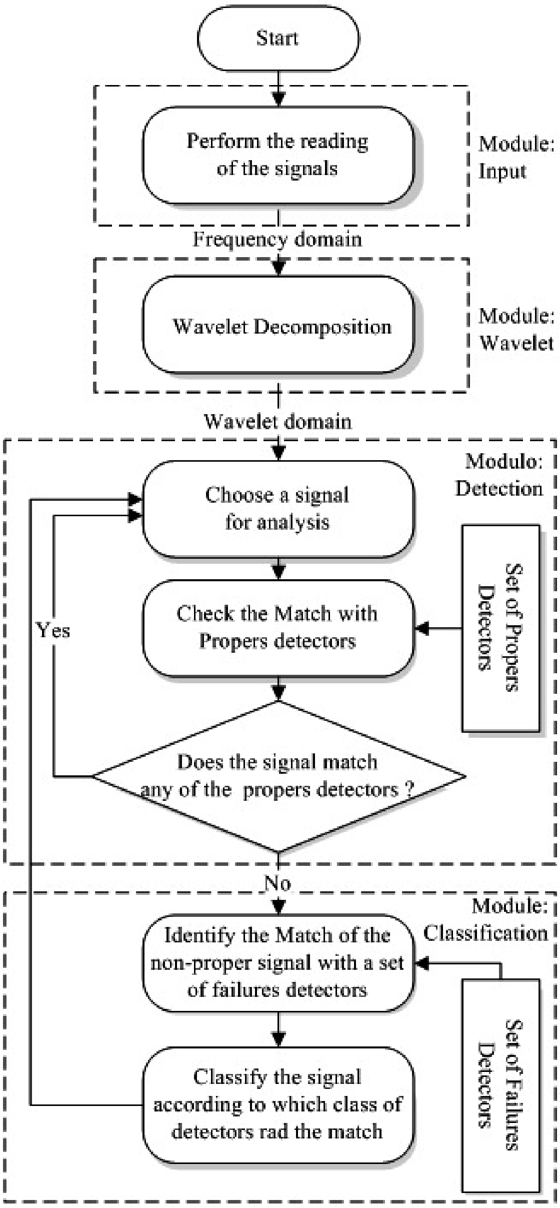
5.2 MONITORING-PHASE

The monitoring-phase is divided into four modules: the input or the reading of the signals (by the acquisition data system), the wavelet module that decomposes the signals into four resolution levels, the detector module, which performs the discrimination of proper/non-proper, and the classification module to classify the failures. Figure 5 illustrates the monitoring-phase.

The wavelet module is executed after the signal is acquired and decomposes the signals, transforming the signals to the wavelet domain. Afterward, the detector module compares the signals that are under analysis with the proper detectors to identify the match with the signals. This module performs the diagnosis of the analyzed signals into proper and non-proper categories.

When an abnormality is detected, the abnormal signal is separated, and the classification module is executed. The classification module compares the abnormal signal with the failures detector set, and the matching is verified. Thus, the abnormal signal is classified according to the detector class that the signal matches.

Figure 5: Flowchart of the monitoring-phase.



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This phase uses the partial matching criterion proposed in [22], adopting a deviation of 3% in the detectors.

5.3 WAVELET DECOMPOSITION MODULE

The wavelet decomposition module is important to extract and emphasize the signal characteristics, which are easily detected in the wavelet world.

In this work, were used four levels of decomposition for the DWT. It was decided to use four levels of decomposition, because with an approximation of four levels in the components of the DWT, the abnormalities in the signals are presented more easily. In the Table 2 is presented the frequency ranges for each level of resolution in the DWT used in this paper.

Figure 6 illustrates a signal with a normal condition and a signal with 15% of damage. These signals were presented at the input of the wavelet decomposition module, and after the signal processing; the resulting signals appears according to Figure 7.

Table 2: Frequency ranges for each level of resolution in the DWT.

Resolution Level	**Parameter**	**Frequency range (KHz)**
1	D_1 component	7.68 – 3.84
2	D_2 component	3.84 – 1.92
3	D_3 component	1.92 – 0.96
4	D_4 component	0.96 – 0.48
4	C_4 component	0.00 – 0.48

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Figure 6: Frequency domain signal.

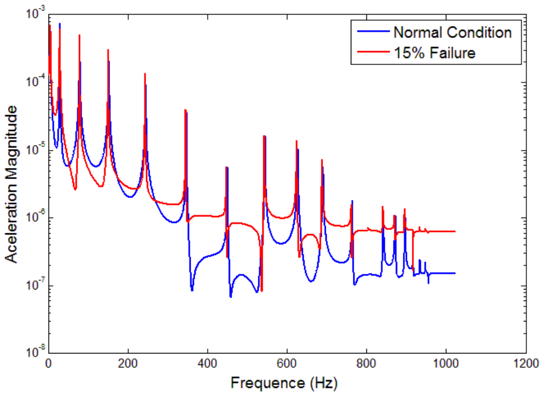

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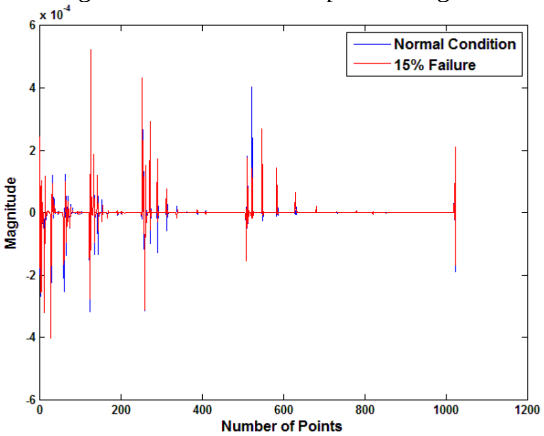
Figure 7: Wavelet decomposition signal.



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These figures show the importance of wavelet decomposition for the diagnosis system. The failures is emphasized when the signal is decomposed in the wavelet world. Thus, the wavelet module contributes to the negative selection algorithm because it is sensitive when analyzing patterns and allows for easy recognition of any abnormality.

6 APPLICATIONS AND RESULTS

This section presents the results that are obtained with the proposed method in the database of test. The algorithm was developed in MATLAB® [28]. The proposed algorithm is applied to a database composed by signals in the frequency domain obtained from a numerical model of an aluminum beam, representing the wing of the aircraft.

6.1 PARAMETER USED IN THE METHOD

In the tests proposed in this work, an assessment of the proposed methodology was applied by checking the efficiency, accuracy and the computational time for different configurations of the set of detectors of the WAIS. In this sense have been generated three sets of detectors (CD_1, CD_2 and CD_3) using 10%, 20% and 30% of the normal signal (base-line), for example, for 10%, 50 signals were selected to be proper detector. In relation to failure detector set, also were used these percentages.

The parameters used for the tests are shown in Table 3.

Table 3: Parameters used in the tests.

Parameters	**Value**
TAf	*66.66%*
Deviation (ε)	*3%*
CD_1	*10% of the data*
CD_2	*20% of the data*
CD_3	*30% of the data*

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6.2 RESULTS

In order to evaluate the proposed methodology, tests were performed considering different settings of the WAIS. The results obtained in the tests are shown in Table 4, and represents the best configuration of the WAIS.

Table 4: Results of the tests.

Analyzed Signals	CD_1		CD_1		CD_1	
	Samples Tests	**Match Correct**	**Samples Tests**	**Match Correct**	**Samples Tests**	**Match Correct**
Normal condition (0%)	500	496	500	498	500	500
5%	150	146	150	148	150	150
10%	150	147	150	148	150	150
15%	150	149	150	149	150	150
20%	150	143	150	147	150	150
25%	*150*	*142*	*150*	*147*	*150*	*150*
30%	*150*	*146*	*150*	*148*	*150*	*150*
Accuracy (%)	97.78		98.92		100%	
Time (*ms*)	96.03		97.32		95.43	

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The results presented in Table 54 represent the average values obtained by a cross-reference test, that was performed 20 times while performing the WAIS for each set of detectors in order to guarantee the veracity of the results.

Was observed that the WAIS has a good performance (accuracy rate equal to 100% for the best configuration), and the quantity of detectors used in censor-phase directly influences the failure diagnosis process. Thus, we suggest using 30% of database information to generate the set of detectors, aiming at providing robustness to the system. That is, the more knowledge available in the learning phase, the more efficient the process of diagnosis of the WAIS.

Finally, we highlight that the WAIS is run with a time of less than 100 milliseconds, which provides the application of this system in real time, as decisions must be taken in time to prevent tragedies and disasters.

6.3 COMPARATIVE STUDY

In this section we present a comparative study with the results of other authors. For this comparison, we took into account the total accuracy of the methodologies for the detection and classification of structural failure.

Table 5 shows the comparison between the total hit obtained by the proposed method and the main methods available in the literature.

Table 5: Comparative study

Reference	Data Type	Technique Used	Accuracy (%)
[10]	Experimental	Multi-objective Genetic Algorithm	93.70
[29]	Experimental	Multilayer Perceptron (Levenberg-Marquardt)	98.52
[7]	Simulated	Fuzzy Logic	98.74
[12]	Simulated	ARTMAP-Fuzzy	100.00
[14, 15]	Simulated	ARTMAP-Fuzzy-Wavelet	100.00
This work	Simulated	WAIS	100.00

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In Table 5, we note that the proposed method in this research had a very good success rate (over 99%), when compared to other methods. Is important emphasize that from the comparison of the results obtained, it is clear that an application in real problem will have a good efficiency.

6.4 POSITIVE AND NEGATIVE ASPECTS OF THE METHODOLOGY PROPOSED

After performing all tests and get the results to the WAIS proposed in this work, we present an analysis highlighting the main positive and negative aspects of the proposed methodology.

Positive Aspects:

- Regarding the accuracy in diagnosing, the WAIS has excellent performance;
- The proposed WAIS runs with low processing time, which accredits this method to be applied in real situations, for decision making should be taken instantly, avoiding disasters;
- The WAIS presented robustness because using 30% of the available information it is able to diagnose almost 100% of actual signals (high level of learning);
- Different from neural networks, in the WAIS is not necessary execute the learning phase (training) every time monitoring runs.

Negative Aspects:

- The WAIS has parameters that must be calibrated, especially in the wavelet module.

7 CONCLUSION

This work presents a new approach to detect and classify failures in aeronautical structures using WAIS algorithm. A numerical model was used to simulate the failures signals, generating a data set to analyzing and test the methodology. The proposed algorithm presents good results, with matching of 100% in detecting and classifying of the failures tested. The generating detector phase is executed off-line with no prejudice for the algorithm. The monitoring-phase is quickly executed in a total time of less than 100 ms, which allows for it to be used in real time to aid the decision making.

The combination of the wavelet transform with the NSA (Negative Selection Algorithm) provides more precision to the diagnosis due to the high-resolution level in decomposing signals, making it easy to identify the abnormalities. Thus, the wavelet immune algorithm that is proposed is precise, robust and efficient and is allowed in several applications, principally in real systems as aircraft structures.

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