Wavelet artificial immune system algorithm applied to the faults aeronautical structural monitoring

Algoritmo do sistema imune artificial Wavelet aplicado a falhas monitoramento estrutural aeronáutico

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ABSTRACT
This paper presents a Wavelet-artificial immune system algorithm to diagnose failures. Basically, after obtaining the vibration signals, 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. 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. The results demonstrate the robustness and accuracy methodology.

Keywords: Wavelet artificial immune systems (WAIS), monitoring and fault identification, aeronautical structures, artificial intelligence.

RESUMO
Este documento apresenta um algoritmo do sistema imunológico Wavelet-artificial para diagnosticar falhas. Basicamente, após a obtenção dos sinais de vibração, é utilizado o módulo wavelet para transformar os sinais no domínio wavelet. Posteriormente, um sistema imunológico artificial de seleção negativa realiza o diagnóstico, identificando e classificando as falhas. A principal aplicação desta metodologia é o processo de inspeção de estruturas auxiliares, a fim de

identificar e caracterizar as falhas. Para avaliar esta metodologia, realizamos a modelagem e simulação de sinais de um modelo numérico de um feixe de alumínio, representando uma estrutura de aeronave. Os resultados demonstram a robustez e a precisão da metodologia.

Palavras-chave: sistemas imunológicos artificiais Wavelet (WAIS), monitoramento 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 (Hall, 1999).

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 (Zheng et al., 2004).

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 (Franco et al., 2009). 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 (Krawezuk et al., 2000), 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 (Giurgiutiu, 2005) is used the method of electro-mechanical impedance to monitor aerospace structures with assets piezoelectric sensors attached. Reference (Palaia, 2007) presents a methodology for structural analysis of buildings using a non-destructive method (NDT). In (Chandrashekhar; Ganguli 2009) is propose a fuzzy system to detect structural faults using curvature mode shapes.

In the work (Xiang-Jun et al., 2010) 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 (Shen et al., 2011). In (Wang et al., 2013) proposed a multimodal genetic algorithm for diagnosing damage in a steel truss bridge. In (Song et al., 2012) the authors propose an experimental method for performing structural analysis of buildings. In (Souza et al., 2013) proposes an ARTMAP-Fuzzy neural network applied in the diagnosis of faults in buildings. Already in (Lima et al., 2013) proposed an immune algorithm with negative selection to diagnose failures in aircraft structures.

Reference (Lima et al., 2014a) was shown a SHM based on ARTMAP-Fuzzy neural network and wavelet transform to diagnose faults in buildings. In (Lima et al., 2014b) a hybrid method based on ARTMAP-Fuzzy neural network and wavelet transform to diagnose failures in aluminum beams was presented. Reference (Abreu et al., 2014) presented a failure analysis tool in aircraft structures using complex wavelet transform.

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 (Castro; Timmis, 2002). As emphasized in (Lima et al., 2014; Souza et al., 2021a), 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 (Campos et al., 2020). 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.

2 NEGATIVE SELECTION ALGORITHM (NSA)

The NSA, which was proposed in (Forrest et al., 1994) 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 (Castro; Timmis, 2002; Castro, 2001; Souza et al., 2021b):

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 (Dasgupta, 1998).

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 (Castro; Timmis, 2002; Dasgupta, 1998).

The antigen (Ag) is the signal to be analyzed in the negative selection algorithm and can be represented by expression (2.1). The detectors represent the antibodies (Ab) and are expressed according to expression (2.2), (Lima et al., 2014, Castro, 2001):

$$Ag = Ag_1, Ag_2, Ag_3, Ag_4, \ldots, Ag_L \tag{2.1}$$

$$Ab = Ab_1, Ab_2, Ab_3, Ab_4, \ldots, Ab_L \tag{2.2}$$

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 (Bradley; Tyrrrell, 2002; Oliveira et al., 2020).

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 (Lima et al., 2014). 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 (Castro, 2001). Reference (Bradley; Tyrrrell, 2002) defines the affinity rate according to the following equation:

$$TAf = \left(\frac{An}{At}\right) * 100 \tag{2.3}$$

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 (2.3) allows the precise calculation of the affinity rate for the proposed problem and represents the statistical analysis with the samples of the problem. Thus, it is possible to quantify the affinity using the patterns, analyzing position-by-position (point-by-point).

Expression (2.4) represents the method for quantifying the total affinity with the analyzed patterns (Lima et al., 2015):

$$Aft = \sum_{i=1}^{L} Pc_i \tag{2.4}$$

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 able to decompose functions, allowing rewriting these functions more detailed, i.e. with a global vision. Thus, it is possible to differentiate local characteristics of a signal in different sizes (resolutions) and, analyze all the signals by translations. As the most of wavelets has compact support, they are useful in analyzing non stationary signals. There are several wavelet families. This work considers the orthonormal family functions and the Daubechies discrete family (Daubechies, 1992) due to have faster computational algorithms (Mallat, 1999).

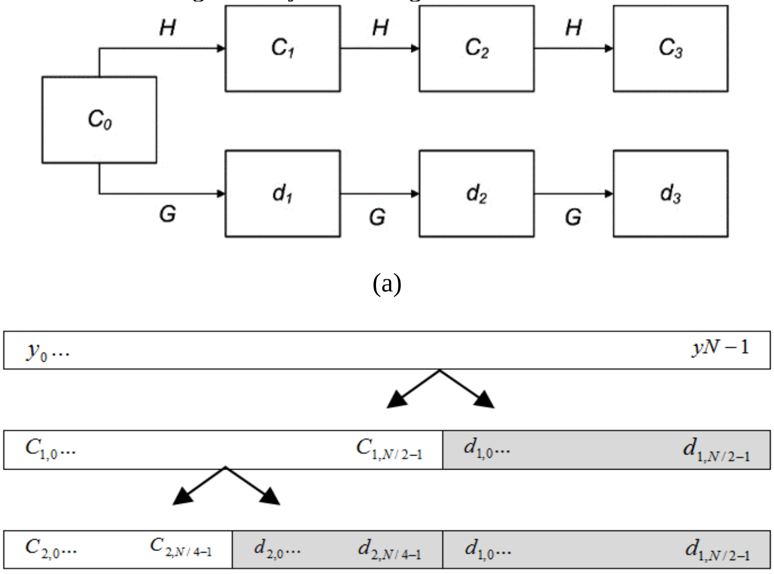
Define a signal $y[t] = (y_0, \dots, y_{n-1}, y_n)$ representing a discrete vector then it can be represented by a wavelet series as follows (Mallat, 1999):

$$y[t] = \sum_{k=0}^{N_J} c_{J,k}\phi_{J,k}(t) + \sum_{j=J}^{1}\sum_{l=0}^{N_j} d_{j,k}\upsilon_{j,k}(t), \nabla t \in [0, N_0] \tag{3.1}$$

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 execute the transformation; *j* is the scale (dilation) and *k* 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), or known as resolution levels. The filters G and H are vectors with constants already calculated that provide an orthogonal base related to the scale and wavelet functions respectively. This process IF known as Mallat Pyramidal algorithm (Mallat, 1999) and is shown in figure 1 (a).

Figure 1. Pyramidal algorithm for DWT.



(b)

At figure 1 (a), C_0 corresponds to the original discrete signal ($C_0 = y[t]$), 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 detail in each resolution level and C_3 are the scale coefficients or approximation at the last level of the transform. These coefficients are obtained by convolution of the constants at filters (3.2) and (3.3), (Mallat, 1999):

$$C_{j+1,k} = \sum_{l=0}^{D-1} h_l C_{j,2k+l} \quad (3.2)$$

$$d_{j+1,k} = \sum_{l=0}^{D-1} g_l C_{j,2k+l} \quad (3.3)$$

where: $k = [0, \ldots, (N/2^j) - 1]$ and D the quantity of constants of 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 run away from the average media. Therefore, the transform coefficients ordered by scale (j) and position (k) are represented as follows (Mallat, 1999):

$$\psi = \left((C_{J,k})_{k=0}^{N_J}, \left((d_{j,k})_{k=0}^{N_J} \right)_{j=J}^{1} \right) \tag{3.4}$$

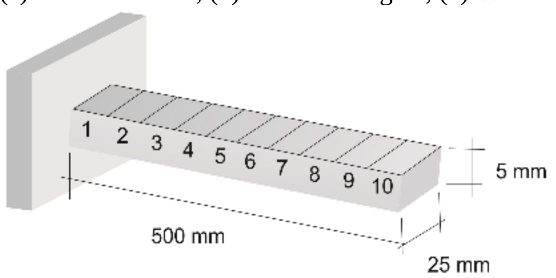
such that ψ is the finite representation in terms of the coefficients of the signal decomposition in equation (3.4). Figure 1 (b) shows the decomposition process of a signal in two resolution levels. Observe that in each transformation level the size of the vectors is reduced by half ($N/2^J$).

4 MODELING AND SIMULATIONS

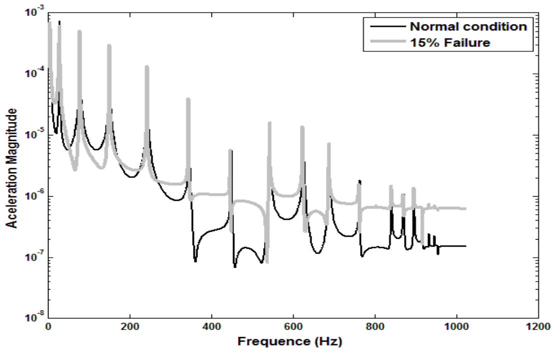
The aluminum beam model proposed to evaluate the methodology, obtained by finite element method, was an aluminum beam in the cantilever-free condition discretized with 10 finite elements with 2 degrees of liberty each. The material properties used are the modulus of elasticity (E = 700 GPa) and the density (γ = 2710 kg/m^3). The dimensions are 500*mm* long, 25*mm* wide and 5*mm* thick. Figure 2 (a) illustrates the patterned beam (Lima et al., 2014c).

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), being 150 signs for each type of failure. The signals at failure were simulated in wear levels 5, 10, 15, 20, 25 and 30%. For each level of wear failure was placed in two locations (finite elements 3 and 5). Figure 2 (b) presents two signals that had been captured in the simulations, the 15% failure and another under ordinary conditions. Following applies wavelet transform to obtain the signals shown in figure 2 (c). The data set is formed by signals processed by the wavelet transform, in the wavelet domain.

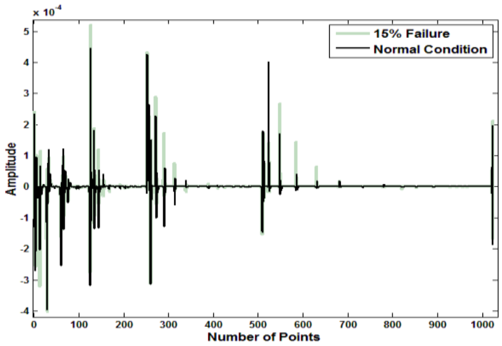
Figure 2. (a) Beam modeled, (b) Simulated signal, (c) Wavelet domain.



(a)



(b)



(C)

5 PROPOSED METHOD

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

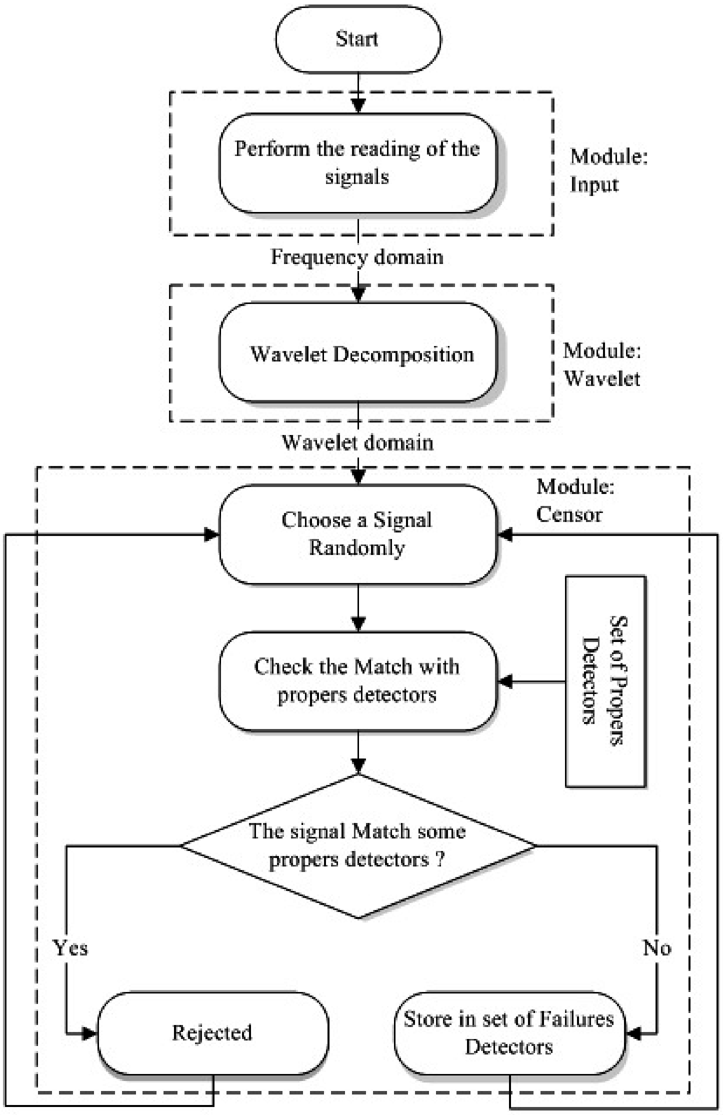
This phase generates the proper detectors and the disturbance detector set. The detector sets are used by the diagnosis system during the monitoring process. The detectors are generated for each kind of signal in the database generated in the modeling and simulation.

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 3.

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 (Lima et al., 2015b), which uses a deviate of 3%.

Figure 3. Flowchart of the Censor phase.



5.2 MONITORING-PHASE

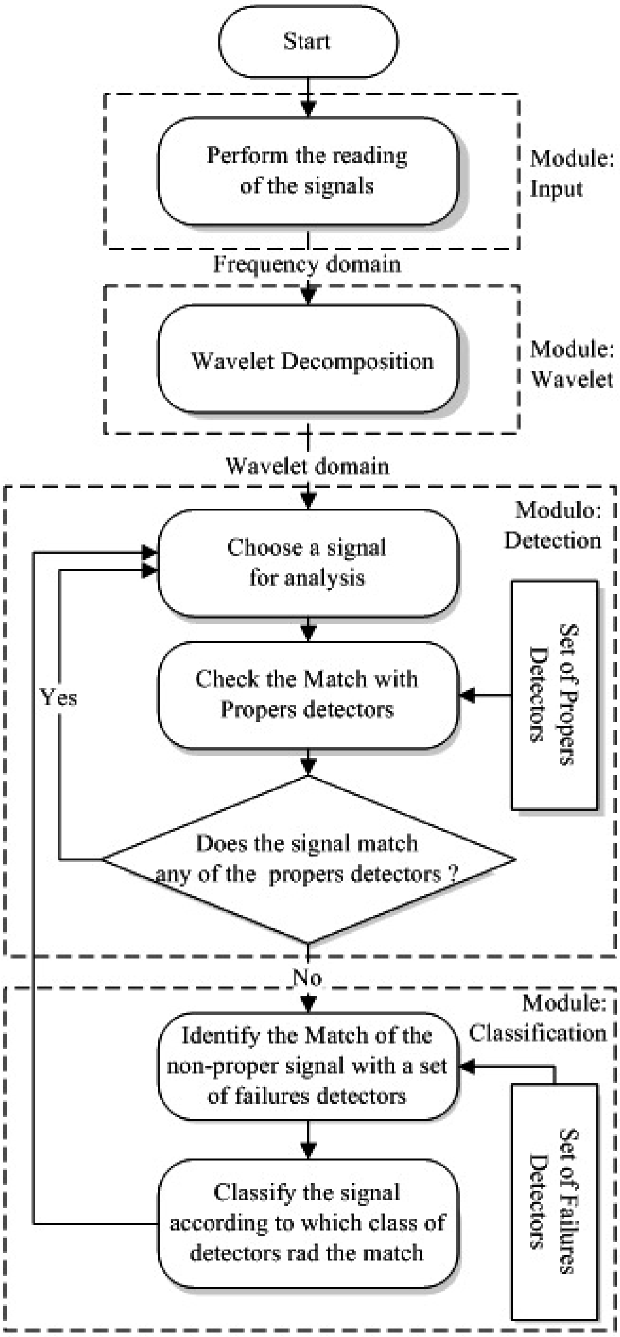
The monitoring-phase is divided into four modules: the input or the reading of the signals (by the acquisition data system), the wavelet module that decomposes the signals into four resolution levels, the detector module, which performs the discrimination of proper/non-proper, and the classification module to classify the failures. Figure4 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 failure's detector set, and the matching is verified. Thus, the abnormal signal is classified according to the detector class that the signal matches.

This phase uses the partial matching criterion proposed in (Bradley; Tyrrrell, 2002), adopting a deviation of 3% in the detectors.

Figure 4. Flowchart of the Monitoring phase.



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 1 is presented the frequency ranges for each level of resolution in the DWT used in this paper.

Table 1. 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

6 RESULTS

This section presents the results that are obtained with the proposed method in the database of test. The algorithm was developed in MATLAB® (MATLAB, 2011). 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 (CD1, CD2 and CD3) 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 2.

Table 2. 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*

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 3, and represents the best configuration of the WAIS.

Table 3. 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	

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

Table 4. Comparative study

Reference	Data Type	Technique Used	Accuracy (%)
(Wang et al., 2013)	Experimental	Multi-objective Genetic Algorithm	93.70
(ROSEIRO et al., 2005)	Experimental	Multilayer Perceptron	98.52
(Chandrashekhar; Ganguli, 2009)	Simulated	Fuzzy Logic	98.74
(Souza et al., 2013)	Simulated	ARTMAP-Fuzzy	100.00
(Lima et al., 2014a)	Simulated	ARTMAP-Fuzzy-Wavelet	100.00
This work	Simulated	WAIS	100.00

In Table 4, 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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