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Article · September 2014

DOI: 10.4028/www.scientific.net/AMR.1025-1026.1107

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Advanced Materials Research Vols. 1025-1026 (2014) pp 1107-1112
© (2014) Trans Tech Publications, Switzerland
doi:10.4028/www.scientific.net/AMR.1025-1026.1107

Submitted: 09.05.2014
Revised: 20.06.2014
Accepted: 05.07.2014

Monitoring and Fault Identification in Aeronautical Structures Using an ARTMAP-Fuzzy-Wavelet Artificial Neural Network

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Keywords: Monitoring and Fault Identification, Aeronautical Structures, Intelligence Computation, ARTMAP-Fuzzy-Wavelet.

Abstract. This paper presents a methodology to perform the monitoring and identification of flaws in aircraft structures using an ARTMAP-Fuzzy-Wavelet artificial neural network**.** This technique is used in the detection and characterization of structural failure. The main application of this method is to assist in the inspection of aircraft structures in order to identify and characterize failures as well as decision-making, in order to avoid accidents or air crashes**.** In order to evaluate this method, the modeling and simulation of signals from a numerical model of an aluminum beam was performed. The results obtained by the method are satisfactory compared to literature.

Introduction

The monitoring and fault identification is a widely employed tool in the aircraft industry, with the aim of ensuring the integrity of structures and avoid disasters. A system for monitoring and fault identification (SHM) carries out tasks such as: acquisition and data processing, validation and analysis, detection, characterization and interpretation of adverse changes in a structure in order to assist decision-making in real time [7]. On aircraft, primarily commercial, structural failures can occur due of various factors, such as component wear, cracks, loosening of bolted joints, or simply the combination of these elements. Such failures in most cases, regardless of origin or intensity, cause a substantial change in the parameters of the structure, causing a reduced structural rigidity, and reduced mass also increased damping so that the dynamic behavior of the structure is changed [14].

Given this problem, several solutions have been proposed, such as ultrasonic inspection, X-radiography, acoustic emission testing, among other traditional techniques of SHM. Such techniques may even have good instrumental equipment and are well formulated, however, cannot meet increasing needs in industry, especially when the structures are in motion [5]. Therefore, to develop a solution for SHMS modern to structures dynamic such as aircraft is the use of smart materials, efficient techniques for processing data and signals, and the use of smart computing techniques.

In this regard, the literature, there are many works available that utilize smart materials and systems in SHM, which feature robustness, accuracy and good performance. Following we present the most relevant papers.

In [8], the authors presented the application of a genetic algorithm in conjunction with a multi-layer perceptron neural network with backpropagation to realize the detection and location of faults in a numerical model of a beam. In the work [6] we used the electromechanical impedance to monitor the aerospace structures coupled with active piezoelectric sensors. In [3] it proposed a fuzzy system to detect structural faults using curvatures of mode shapes of vibration. A system for identifying and locating damages in an aircraft wing utilizing a probabilistic neural network proposed in [13]. In [15] it was proposed the multimodal genetic algorithm to diagnose damages in a steel truss bridge. The work [10] proposed an ARTMAP-*Fuzzy* neural network for monitoring the integrity of mechanical structures (beams). In [9] it proposed an immune negative selection algorithm to diagnose faults in aircraft structures.

This paper presents a new approach for monitoring and fault identification in aircraft structures using an ARTMAP-Fuzzy-Wavelet neural network. From acquisition and processing of the signals, applies an ARTMAP-Fuzzy-Wavelet neural network to identify and characterize structural failure. To evaluate this method, we used a database of simulated signals from a numerical model of a beam of aluminum, which in this case is the structure of the wing of an aircraft. The beam was modeled by finite elements and simulated using Matlab [11]. The combination of wavelet transform with ARTMAP-Fuzzy neural network enables greater precision when diagnosing faults because the signals are decomposed into several levels of resolution, so that the signals are analyzed in detail, facilitating the identification of failures.

Artificial Neural Network Artmap-*Fuzzy*

The ARTMAP-*Fuzzy* artificial neural network, has an architecture based on adaptive resonance theory, ie, belongs to the family ART [1]. This network corresponds to a supervised learning system consists of a pair of modules of adaptive resonance theory, ART_a-*Fuzzy* and ART_b-*Fuzzy*, which receive and classify the inputs (I_a) and desired outputs (I_b) respectively, and the inter-ART associative memory module verifies the matching criterion of the inputs and outputs to the existing categories. Fig. 1 illustrates the architecture of ARTMAP-*Fuzzy* neural network [2].

The basic parameters of the ARTMAP-*Fuzzy* neural network are [2]:

- Parameter choice α ($\alpha > 0$): Operates in the category selection;
- Rate Training β ($\beta \in [0\ 1]$): Controls the speed of adaptation of the network;
- Parameter monitoring (ρ_a, ρ_b e ρ_{ab} $\in$ [0 1]): Controls the resonant network, namely the parameter responsible for the number of categories created.

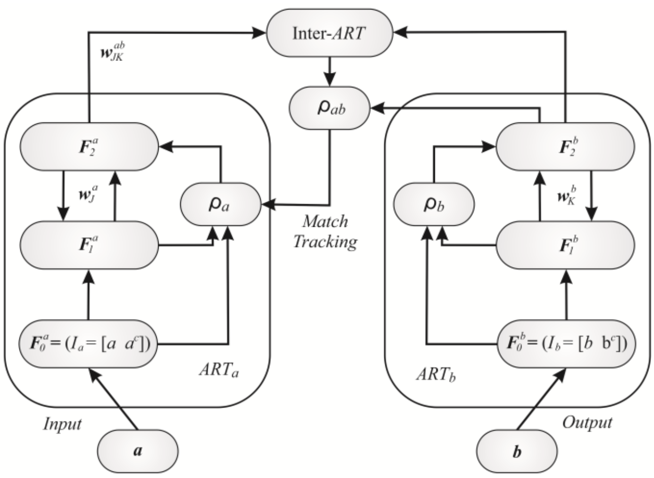


Fig. 1 ARTMAP-Fuzzy neural network [2].

Discrete 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 [4] due to have faster computational algorithms [12].

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 [12]:

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

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 [12] and is shown in Fig. 2 (a).

At Fig. 2 (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 (2) and (3), [12]:

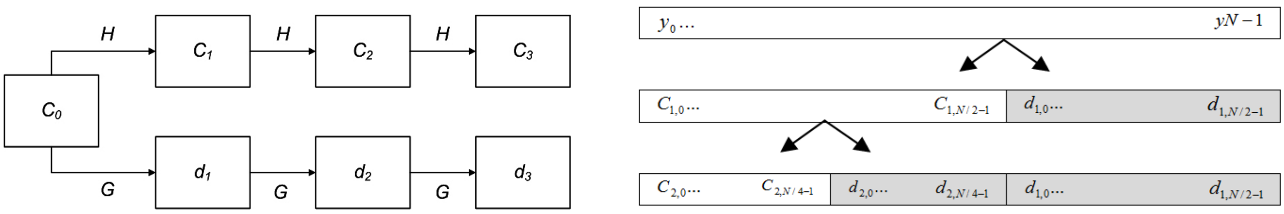
$$C_{j+1,k} = \sum_{l=0}^{D-1} h_l C_{j,2k+l} \tag{2}$$

$$d_{j+1,k} = \sum_{l=0}^{D-1} g_l C_{j,2k+l} \tag{3}$$

where: $k = [0, \dots, (N/2^j) - 1]$ 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 [12]:

$$\psi = \left((C_{J,k})_{k=0}^{N_J}, \left((d_{j,k})_{k=0}^{N_J}\right)_{j=J}^{1}\right) \tag{4}$$

such that ψ is the finite representation in terms of the coefficients of the signal decomposition in equation (1). Fig. 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 ($N/2^J$).



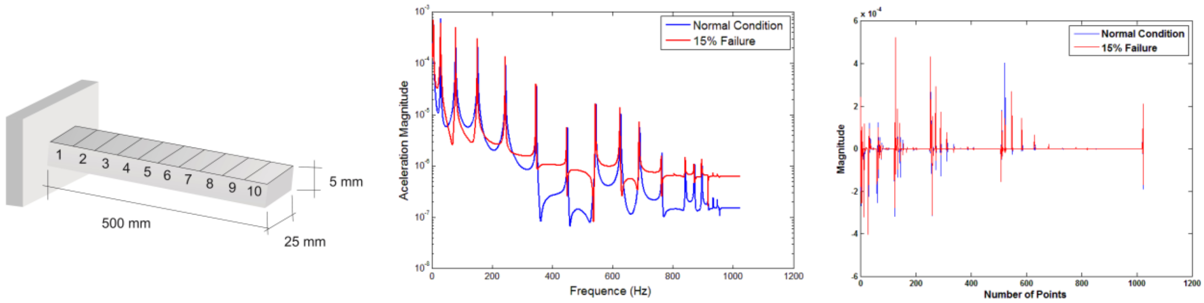
(a) (b)

Fig. 2 Pyramidal algorithm for DWT [12]

Modeling and Simulations

The proposed model 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. Fig. 3 (a) illustrates the patterned beam [9].

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 850 signals in the structure, 500 without wear (base-line condition) and 350 signs with wear (structural failure). The signals at failure were simulated in wear levels 1, 5, 10, 15, 20, 25 and 30%. For each level of wear failure was placed in two locations (finite elements 3 and 5). Table 1 shows the number of simulations for each level of failure. Fig. 3 (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 Fig. 3 (c). The data set is formed by signals processed by the wavelet transform, in the wavelet domain.



(a) (b) (C)

Fig. 3 (a) Beam modeled, (b) Simulated signal, (c) Wavelet domain.

Table 1 Settings of the simulations

Wear Level	0%	1%	5%	10%	15%	20%	25%	30%	Total
Number of simulations	500	50	50	50	50	50	50	50	850

Proposed Methodology

The system of monitoring and fault diagnosis is proposed in this paper consists of four main modules: data acquisition, the wavelet decomposition, training and diagnosis of ARTMAP-*Fuzzy* neural network.

The data acquisition module is composed of the experimental apparatus for capturing the signals on the mechanical structure, such as sensors, actuators, accelerometers, etc. The signals are representing the frequency response obtained by the data acquisition module.

Further, the signals are processed by Wavelet decomposition module at three levels of resolution. The set of signals obtained in the wavelet domain are used as inputs to the ARTMAP-*Fuzzy* neural network.

The module of training the ARTMAP-*Fuzzy* neural network is performed *off-line* and serves to adjust the weights and create categories (knowledge) to be used in diagnostic data. In this module, the network is trained using a data set is generated and a number of categories equals the number of input signals.

The diagnostic module is performed *online*. In this module, a new set of signals from different set of signals used in the training phase the network should be presented, and each signal will be analyzed individually. All signals are compared with the knowledge (categories created in the training phase) obtained by the ARTMAP-*Fuzzy* neural network-so when there is a marriage between the defaults is classified in the category signal presented to ARTMAP-*Fuzzy* network. Obtained the corresponding category a certain pattern is therefore identified intensity (percentage of failure) and the location of the fault in the structure. The flowchart of the functioning of the monitoring and fault diagnosis system is presented in Fig. 4.

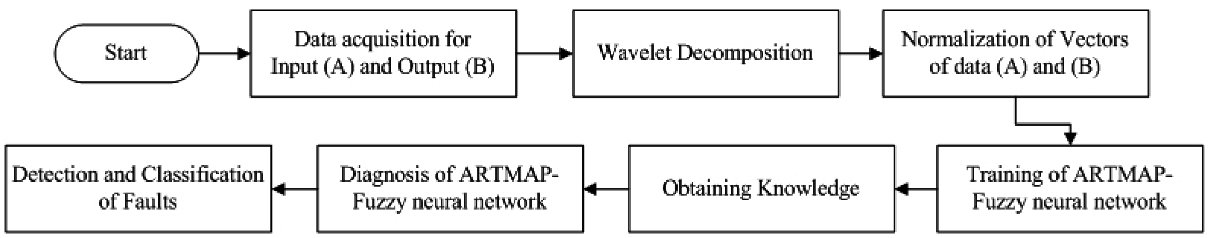


Fig. 4 Proposed Methodology

Applications and Results

In this section, we present the results obtained with the application of ARTMAP-Fuzzy-Wavelet neural network in the database. All tests were performed using a PC Intel Core 2 Duo 1.9 GHz, 2GB of RAM, operating system Windows 7 Ultimate 32 bits. The algorithm was developed in MATLAB® [11].

To test the ARTMAP-Fuzzy-Wavelet neural network was proposed analyzed the efficiency, accuracy and computation time in fault diagnosis process on the simulations performed. The parameters of the fuzzy-ARTMAP neural network-wavelet utilized in the training and diagnosis process were $\alpha = 0{,}2$, $\beta = 0.9$, $\rho_a = 0{,}8$, $\rho_b = 1$ and $\rho_{ab} = 1$.

In the training phase we used a data set with 595 signs, 350 signs of the structure under normal conditions (base-line) and 245 signs of structure failure. This data set corresponds to 70% of the available data. To evaluate ARTMAP-Fuzzy-Wavelet neural network in the diagnosis phase was used a data set with 2550 signals, 150 signals of the structure without fail and 105 signal failure of the structure. These data used in the tests represent 30% of the available data. The database simulated has seven different patterns faults. The signals obtained by Wavelet decomposition represent the input signals to the training and diagnosis of ARTMAP-Fuzzy-Wavelet neural network. Table 2 shows the results obtained by the system failure diagnosis in structures when applied to the data set.

Table 2 Results obtained by the method

	Training Phase	Diagnostic Phase
Samples Used	595	255
Ratings Correct	595	255
Ratings Wrongs	0	0
Accuracy (%)	100,00	100,00
Time (*ms*)	915,82	194,63

To obtain these results, the system has undergone a testing phase and parameter settings. The results were obtained with the best configuration of ARTMAP-Fuzzy-Wavelet neural network. The result was obtained by cross-reference test, in which the system was run 15 times to ensure accuracy of results. We note that the analysis of the structural integrity shows a good performance, with a success rate of 100%. It is noteworthy that the wavelet module provided a more detailed analysis of the signals, so that the failures were easily identified.

Conclusion

In this article, a new approach has been proposed in order to analyze the structural integrity of aeronautical structures, in which we used an ARTMAP-Fuzzy-Wavelet artificial neural network who presented excellent results, obtaining a hit rate of 100% for the best system configuration. The training phase is the one that requires more computational time; however is executed *off-line* causing no harm to the algorithm. Already the diagnostic phase of the system, from the acquisition of signals and wavelet processing is performed rapidly below 200 milliseconds, which entitles the system to be a tool used in real time. It is noteworthy that the wavelet module allows perform the analysis of the signals in a different domain, in which faults are easily identified due to the coefficients of detail of the multi-resolution analysis. Finally, it is concluded that the ARTMAP-Fuzzy-Wavelet artificial neural network proposed is very efficient, reliable and robust in the integrity analysis of aeronautical structures.

Acknowledgements

The authors thanks Conselho Nacional de Pesquisas (CNPq Proc. n. 301769/2012-5) and Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) for financial supports.

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