

**DIAGNOSIS OF FAILURES IN AERONAUTICAL
STRUCTURES USING A NEW APPROACH HYBRID BASED
IN ARTIFICIAL NEURAL NETWORKS AND
WAVELET TRANSFORM**

Simone S.F. Souza¹ §, Fernando P.A. Lima², Fábio R. Chavarette³

UNESP - Univ. Estadual Paulista

Faculty of Engineering of Ilha Solteira

Department of Mathematics

Brasil Avenue, 56, 15385-000, Ilha Solteira, SP, BRAZIL

Abstract: This paper presents a new hybrid methodology to diagnose failures in aeronautical structures using as a tool the Perceptron multi-layer artificial neural networks and ARTMAP-Fuzzy and the wavelet transform. The main application of this hybrid methodology. 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. The results demonstrate the robustness and accuracy of the methodology.

AMS Subject Classification: 68W40, 42C40

Key Words: hybrid methodology, structural health monitoring, intelligent systems

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

Received: November 3, 2017

Revised: September 24, 2018

Published: September 30, 2018

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url: www.acadpubl.eu

§Correspondence author

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 [5]. 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 [14].

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 smart materials and 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. Giurgiutiu [4] used the method of electro-mechanical impedance to monitor aerospace structures with assets piezoelectric sensors attached. A system for the identification and location of damage to an airplane wing using a probabilistic neural network was proposed in [11]. In [12] proposed a multimodal genetic algorithm for diagnosing damage in a steel truss bridge. Already in [7] proposed an immune algorithm with negative selection to diagnose failures in aircraft structures.

In [8] a hybrid method based on ARTMAP-Fuzzy neural network and wavelet transform to diagnose failures in aluminum beams was presented. Abreu et al. [1] presented a failure analysis tool in aircraft structures using complex wavelet transform. In [9] was proposed an artificial immune system with wavelet transform to diagnosis of structural failures.

In this paper, presents a new approach to fault diagnosis in aeronautical structures using a hybrid method based on artificial neural networks (ANN) Perceptron Multi-Layer and ARTMAP-Fuzzy and the wavelet transform. This methodology is divided into three main modules, with the acquisition and processing of data, fault detection and classification. In this work we applied the Perceptron Multi-Layer ANN and ARTMAP- Fuzzy because of the quality and efficiency of both ANNs, as shown in other studies, for pattern recognition and diagnosis. The use of the wavelet transform provides a more sensitive diagnostic

system, where the presence of abnormalities in the signal is identified easily. In order to evaluate the proposed methodology, was used a mathematical model of an aluminum beam. The structure was modeled by finite elements and simulated. The results demonstrate the efficiency, accuracy and robustness of the proposed method.

2. Multi-Layer Perceptron and Backpropagation Algorithm

The Perceptron Multi-Layer (PML) ANN corresponds to a parallel processor composed neurons (processing units). Neurons are arranged in one or more layers interconnected by a large number of connections. The connections are associated with weights representing knowledge. The learning of PML network is named training and occurs by adjusting the weights. The common learning is performed using a training algorithm. In this work we adopted the backpropagation algorithm, which is the best known algorithm for training PML networks. The backpropagation algorithm is a supervised learning technique that utilizes pairs (input and desired output) for through the Error calculation, adjust the weights of the network and gain knowledge [6]. In more detail, the process of learning the MLP network using backpropagation is run through the following steps [13]:

1. The start with random values and nonzero the weights;
2. Show a pattern of input and propagate it to the exit of the network;
3. Calculate the instantaneous error at the network output (E), wherein (1) represents the calculation of error of each neuron network at time n, and (2) is the calculation of the total error at time n;

$$e_j(n) = d_j(n) - y_i(n). \quad (1)$$

$$E(n) = \frac{1}{2} \sum_{j=1}^m e_j^2(n). \quad (2)$$

4. Calculate the local gradients (δ) of the neurons of the output layer, given by (4). The gradient of neuron j is the product resulting from the error

of neurons (j) to the derivative of the activation function (Q') applied to the local field induced v_j calculated in (3) where w_{ij} is the weight input is associated with each neuron j;

$$v_j(n) = \sum_{i=0}^m w_{ij}(n) - y_i(n). \quad (3)$$

$$\delta_j(n) = e_j(n)Q'(v_j(n)). \quad (4)$$

5. Adjust the output layer weights using the expressions (5):

$$\Delta w_{ij}(n) = \eta \delta_j(n) y_i(n) \quad (5)$$

$$w_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij}(n) \quad (6)$$

6. Calculate the local gradients of neurons in the hidden layer using (7), where p refers to the number of neurons connected to the right j:

$$\delta_j(n) = Q'(v_j(n)) \sum_{k=1}^p \delta_k(n) w_{kj}(n) \quad (7)$$

7. Adjust the weights of the hidden layer using the expressions in (8);

$$\Delta w_{ji}(n) = \eta \delta_j(n) y_i(n) \quad (8)$$

$$w_{ji}(n+1) = w_{ji}(n) + \Delta w_{ji}(n) \quad (9)$$

8. Repeat steps 2-7 for all training patterns (1 epoch);
9. Calculate every epoch the mean square error (MSE) for the training using the expression (10), where N is the number of patterns used for training;

$$MSE = \frac{1}{N} \sum_{j=1}^N E(j) \quad (10)$$

10. If the MSE is greater than the desired value (DV) or whether the time counter is less than the maximum number of times (MNTp) repeat step 8. Otherwise stop;

3. ARTMAP-Fuzzy Artificial Neural Networks

The ARTMAP-*Fuzzy* artificial neural network corresponds to a supervised learning system comprised of a pair of modules Adaptive Resonance Theory, $ART_a - Fuzzy$ and $ART_b - Fuzzy$, interconnected by inter-ART associative memory module. This neural network architecture incorporates *fuzzy* set theory, the AND *fuzzy* operator ($\wedge$) enabling the learning of the neural system in response to binary input patterns and analog, belonging to the interval $[0\ 1]$ [2].

A internal mechanism called match-tracking is responsible for self-regulating process of the neural network, in which maximize generalization and minimize the error. When the neural network makes a prediction wrong, through an associative connection instructed, the monitoring parameter of $ART_a - Fuzzy$ module is incremented in minimum amount necessary to correct the error in the $ART_b - Fuzzy$ module.

The ARTMAP-*Fuzzy* architecture has three main parameters for the development, namely, parameter choice α ($\alpha > 0$), rate training β ($\beta \in [0\ 1]$) and parameter monitoring ($\rho_a, \rho_b \in \rho_{ab} \in [0\ 1]$) [2]. If ρ has a large value, the neural network becomes more selective reducing its generalizability. If ρ has a small value, it reduces the number of categories created, increasing the generalization capability of the ARTMAP-*Fuzzy* network.

4. 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. 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 [10]:

$$y[t] = \sum_{k=0}^{N_J} C_{J,k} \phi_{J,k}(t) + \sum_{j=J}^1 \sum_{l=0}^{N_j} d_{j,k} v_{j,k}(t), \forall t \in [0, N_0] \quad (11)$$

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 $v_{j,k}(t)$ 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 is known as Mallat Pyramidal algorithm [10] and is shown in Figure 1.

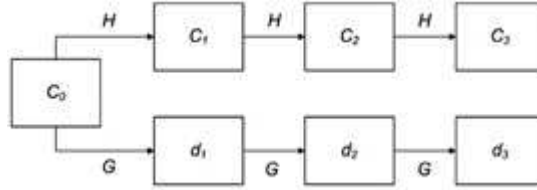


Figure 1: Pyramidal algorithm for DWT.

Figure 1, 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 (12) and (13) [10]:

$$C_{j+1,k} = \sum_{l=0}^{D-1} h_l C_{j,2k+l} \quad (12)$$

$$d_{j+1,k} = \sum_{l=0}^{D-1} g_l C_{j,2k+l} \quad (13)$$

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 [10]:

$$\psi = ((C_{j,k})_{k=0}^{N_j}, ((d_{j,k})_{k=0}^{N_j})_{j=J}^1) \quad (14)$$

such that ψ is the finite representation in terms of the coefficients of the signal decomposition in equation (14).

5. 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 ($E = 700GPa$) and the density ($\gamma = 2710kg/m^3$). The dimensions are $500mm$ long, $25mm$ wide and $5mm$ thick. Figure 2 illustrates the patterned beam [9].

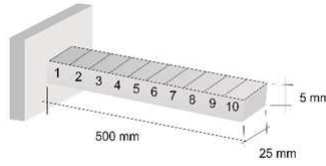


Figure 2: Beam modeled.

The detection module is performed by the Multi-Layer Perceptron ANN using the knowledge gained in the training process to differentiate the signals in normal and abnormal. When a normal signal is detected, is automatically classified as a base-line condition of the structure (structure without fail). When an abnormal signal is detected the classification module is triggered in order to characterize the type of failure identified.

The classification module is performed by ARTMAP-*Fuzzy* ANN and aims to characterize the type of fault detected. In this process the ARTMAP-*Fuzzy* ANN use the knowledge gained in the training phase and classifies the abnormality identified in a simulated fault levels for the available databases.

We emphasize that for the process of training the neural network is used a different set of data from the data presented in the monitoring process.

6. Applied and Results

6.1. Configuration and Parameters

The Multi-Layer Perceptron ANN was modeled with 1024 neurons in the input layer, 1200 in the intermediate layer and 2 in the output layer. The parameters used for the Multi-Layer Perceptron ANN were $MNTp = 10^4$, $DV = 10^{-6}$ and the parameters used for the ARTMAP-*Fuzzy* ANN were $\alpha = 0.2$, $\beta = 0.9$, $\rho_a = 0.8$, $\rho_b = 1$ and $\rho_{ab} = 1$.

For training the ANNs were used 70% of the data available, with 900 signs, of which 600 (300 signs the structure in normal condition and 50 signals for each level fault) for Multi-Layer Perceptron ANN and 300 (50 signals for each level fault) to the ARTMAP-Fuzzy ANN. The testing phase (monitoring) were used 30% of the remaining data (500 signals), of which 200 structure in normal condition and 300 failure in the structure (50 signals for each level fault).

6.2. Results for the Aluminum Beam Model

Table 1 shows the results obtained by the proposed hybrid system, when applied to the data set of the aluminum beam.

	Training Multi-Layer Percepytron		Training ARTMAP-Fuzzy		Dianostic	
Signals	Samples	Ratings	Samples	Ratings	Samples	Ratings
Normal	Used	Correct	Used	Correct	Used	Correct
condition	300	300	-	-	200	20
5%	50	50	50	50	50	50
10%	50	50	50	50	50	50
15%	50	50	50	50	50	50
20%	50	50	50	50	50	50
25%	50	50	50	50	50	50
Acuracy %	100.00		100.00		100.00	
Time (s)	3125.12		0.623		0.236	

Table 1: Results obtained by the proposed methodology.

The proposed hybrid system showed an excellent performance, with a 100% success rate in detecting and classifying faults to the problem of aluminum beam.

7. Conclusion

In this paper we propose a new hybrid approach based on Multi-Layer Perceptron ANNs and ARTMAP-Fuzzy and the wavelet transform to diagnose failures in aeronautical structures. In this context the hybrid system showed excellent results by getting a 100% success rate for the best system configuration for both analyzed problems. The learning phase of ANNs (training) requires more computational time; however, is executed off-line causing no damage to the system.

Already the phase of monitoring is carried out rapidly with time less than 250 milliseconds. We emphasize that the processing performed with the wavelet transform provides increased efficiency to the system, because the decomposing signals into 3 levels of resolution, the abnormalities are easily identified. Finally, we conclude that the hybrid methodology proposed is very efficient, reliable and robust for fault diagnosis in aeronautical structures.

Acknowledgment

The authors thanks all the support of the SisPlexos Laboratory.

References

- [1] C.C.E Abreu, F.R. Chavarette, F.V. Alvarado, M.A.Q. Duarte, F.P.A. Lima, Dual-Tree Complex Wavelet Transform Applied to Fault Monitoring and Identification in Aeronautical Structures, *International Journal of Pure and Applied Mathematics*, **97**, (2014), 89-97, doi: 10.12732/ijpam.v97i1.9.
- [2] G.A. Carpenter, S.Grossberg, N. Markuzon, J.H. Reynold, D.B. Rosen. Fuzzy ARTMAP: A neural network for incremental supervised learning of analog multidimensional maps, *IEEE Transactions on Neural Network*, **3**, 5, (1992), 689-713.
- [3] V.R. Franco, D.D. Bueno, H.J. Brennan, A.A. Cavalini Jr, C.G. Gonsalez, V.Lopes Jr. Experimental damage location in smart structures using Lamb waves approaches. *Proceedings of the Brazilian Conference on Dynamics, Control and Their Applications*, (2009), 1-4.
- [4] V. Giurgiutiu. Tuned lamb wave excitation and detection with piezoelectric wafer active sensors for structural health monitoring, *Journal of Intelligent Material Systems and Structures*, **16**, 4, (2005), 291305.
- [5] S.R. Hall. The effective management and use of structural health data, *Proceedings of the International Workshop on Structural Health Monitoring*, (1999), 265-275.
- [6] S.H. Haykin, *Neural Networks: A comprehensive foundation*, MacMilliam College Publishing, New York. (1994).
- [7] F.P.A.Lima, F.R. Chavarette, A.S.Souza, S.S.F.Souza, M.L.M. Lopes. Artificial Immune Systems with Negative Selection Applied to Health Monitoring of Aeronautical Structures, *Advanced Materials Research*, **871**, (2013), 283-289.
- [8] F.P.A.Lima, F.R. Chavarette, S.S.F.Souza, M.L.M. Lopes, A.E. Turra, V. Lopes Jr. Monitoring and Fault Identification in Aeronautical Structures Using an ARTMAP-Fuzzy-Wavelet Artificial Neural Network, *Advanced Materials Research*, **1025-1026**, (2014), 1107-1112.
- [9] F.P.A.Lima, F.R. Chavarette, S.S.F.Souza, M.L.M. Lopes. Monitoring and Fault Identification in Aeronautical Structures Using an Wavelet-Artificial Immune System Algorithm, In: Tephem Ekwaro-Osire, Aparecido C. Gonalves, Fisseha M. Alemayehu. (Org.). *Probabilistic Prognostics and Health Management of Energy Systems*. 12ed. So Paulo: Springer International Publishing, **1**, (2017), 1-17.

- [10] S. Mallat, *A Wavelet tour of signal processing*, Academic Press, **2**. New York, (1999), 637p.
- [11] T. Shen, F. Wan, B. Song, Y. Wu, Damage Location and Identification of the Wing Structure With probabilistic neural Networks. *Proceedings of the Prognostics and System Health Management Conference*, (2011), 16.
- [12] F. L. Wang, T.H.T. Chan, D.P.Thambiratnam, A.C.C. Tan, Damage Diagnosis for Complex Steel Truss Bridges Using Multi-Layer Genetic Algorithm, *Journal of Civil structural Health Monitoring*, Springer-Verlag, (2013), 117217.
- [13] P.J. Werbos. *Beyond regression: New tools for prediction and analysis in the behavioral sciences*, PhD. Thesis, Harvard University, (1974).
- [14] S. Zheng, X. Wang, L. Liu, Damage detection in composite materials based upon the computational mechanics and neural networks, *Proceedings of the European Workshop on Structural Health Monitoring, Munich*, (2004), 609615.