Diagnostic System Validation for Damage Monitoring of Helicopter Fuselage

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ABSTRACT

Fatigue assessment for helicopter structures is nowadays a design matter, confirmed during the operating life of the machine with a clear inspection schedule, thus requiring many machine stops and causing a steep increase of maintenance efforts, which arise up to 25% of the whole operating costs. A direct health monitoring system able to correctly estimate damage likelihood, position, extent, thus coming to the evaluation of the residual useful life (RUL) of the monitored region is missing. It could lead to real time knowledge about the damage condition, allowing the Condition Based Maintenance (CBM) and maximizing both machine availability and safety. The work presented in this article is about the creation of a diagnostic for helicopter fuselage Structural Health Monitoring. The main characters involved are Finite Element Models (FEM) and algorithms, the former providing a low cost knowledge upon which training the algorithms (multilayer Artificial Neural Networks) in detecting, localizing and quantifying the damage. The FEM based diagnosis can also be used for a preliminary assessment of the algorithm performances, before any real test is executed, thus allowing for a significant cost saving. The methodology demonstration is described, thus appreciating the real performances of the method for a specimen which is representative of the helicopter fuselage, consisting of an aluminum skin stiffened through some riveted stringers. A sensor network has been designed in order to detect any fatigue damage occurring on the structure, then activating the algorithms for damage characterization, in terms of crack position and length.

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INTRODUCTION

In recent years the problem of structural monitoring for the health assessment of the operating aircrafts has become a critical research topic [1][2][3][4]. In particular, helicopters are very critical aircrafts from a fatigue standpoint. As a matter of fact they are subjected to a high number of load cycles. From one hand, low frequency load cycles, due to maneuvers of the helicopter, are characterized by a high amplitude and are responsible for crack nucleation and propagation. From the other hand, high frequency load cycles, due to the rotor aerodynamic interaction with the air, are also transmitted to the airframe. Though it is crucial that structures would be designed in a way that avoids high frequency cycles participating to crack propagation, it could happen that if a crack propagates on the structure (because of maneuver loads) it will generate a high stress intensification, thus becoming sensible also to high frequency loads. This can cause a sudden failure of the considered region. In addition, the harsh environment where the helicopter operates is responsible for corrosion and consequently massive crack nucleation.

As a consequence, the maintenance of helicopter structures is critical because it requires very strict intervals for manual structure scanning, often requiring dismounting of large portions of the aircraft. The availability of the helicopter is thus the key parameter that wants to be optimized. The disposal of a compound methodology for the automatic assessment of structural health, able to detect critical damages and to characterize them allowing for the residual useful life prognosis, would revolutionize the actual maintenance procedures. As a matter of fact, a smart network of sensors can be installed on the structure in order to detect, localize and quantify crack damages, without requiring any structure dismounting and possibly allowing for an on-board SHM. Also the safety parameters could receive some benefits from this approach, as this monitoring system might be able to provide continuous information to the pilot (or to the maintenance center), thus assisting the user in the decision on whether to stop a mission or to proceed until the next scheduled maintenance.

However, many attempts to realize automatic SHM system have been carried out, based on many technologies, among which the soundest approaches rely on mechanical diagnostic wave propagation in structure [5][6], acoustic emission, vibration monitoring, strain field measure [7], comparative vacuum monitoring [8], etc. Any approach has its advantages and drawbacks. Nevertheless a common problem is that the costs associated to the tests for the interpretation of the acquired signal and for crack feature extraction are very high. Especially when dealing with aeronautical structures constituted by riveted metallic skin panels, it is important to consider that the possibilities for crack position are widespread, thus requiring a huge test campaign. Inside this framework, Finite Element Models can be used to generate the necessary experience for the interpretation of the raw sensor data acquired from the smart sensor network. The approach consists in generating a database of many damage models (with variable crack center position and crack length), to be used to train an Artificial Neural Network (ANN) system. The advantage of FEM is not only the possibility to retrieve information about a huge number of damage cases, but also the possibility to obtain a preliminary assessment of the diagnostic performances of the system. With the term “performances”, one could indicate the following points:

- minimum detectable crack length as a function of crack position
- crack length quantification error
- crack center position error

A diagnostic system based upon strain field measures is the object of this study. It consists of a series of ANNs trained with FEM simulations of crack damages in order to detect a structural anomaly (crack), then to quantify and to localize the damage. The diagnostic system is installed on a typical aluminium structure constituted by a skin stiffened through some riveted stringers (Figure 1), representative of the rear fuselage of a helicopter. The procedure for sensor network design has been addressed in [9], coming to the sensor web configuration shown in Figure 1. The optimization of the diagnostic algorithm performances has been reported in detail in [10]. The first part of this paper is about the presentation of the FE model, the algorithm structure and the experimental tests. Follows a second part in which the validation of the detection algorithm performances, previously evaluated with only the adoption of FEM simulations, is performed.

Figure 1. Typical aeronautical panel consisting in a skin stiffened through some riveted stringers. 20 FBG sensors have been applied to monitor crack propagation.

PART I: THE FEM-BASED DIAGNOSTIC SMART UNIT

The first part of the paper is aimed at defining the SHM problem at issue. The sensors, the smart signal processing algorithms and the Finite Element models (FEM) are the three elements in this framework, each of them playing a significant role within the diagnostic system. Distributed sensors are organized as a network and provide signals to be interpreted for diagnostic and prognostic purposes by means of the smart algorithm. Algorithms for signal processing are the "brain" of the SHM. They receive the sensor data as a real-time input, and treat them statistically in order to infer the structural health condition of the monitored region. However, if only a statistical interpretation of the raw sensor data is adopted, an a priori definition of the thresholds for the pattern classification is often required and the association of a physical condition (i.e. crack length or position) to the classified instance is often difficult. Finite Element Models are the solution to these problems. Finite Element simulations represent the "virtual experience" of the SHM. They provide some basic (and relatively low cost) information that can be used to train the algorithms to understand the physical reality behind raw sensor data.

The Finite Element Model

The validated FE model used to simulate the real structure behaviour is shown in Figure 2. The structure consists of an aluminium skin, stiffened through some riveted stringers. Skin and stringer thicknesses have been set respectively to 0.81mm and 1mm. Both stringers and skin have been modelled with quadratic shell elements (S9R5), while rivets have been simulated through three-axes springs. Each stringer has been connected to the skin by means of 20 rivets and the distance between two stringers is 150mm. In addition, the upper and lower portions of the model have been designed in order to simulate the connections to the actuator and to the ground. The gripping system has been designed to distribute the load to both the stringers and the skin, thus allowing the simulation of stress and strain in the real fuselage. Two hundred randomly positioned cracks have been modelled for each 10mm crack length step, ranging from 20mm to 100mm. A parametric script (with variables crack center position and crack length) has been run in ABAQUS 6.9 software to obtain the information needed in terms of damage dependent strain field for each case.

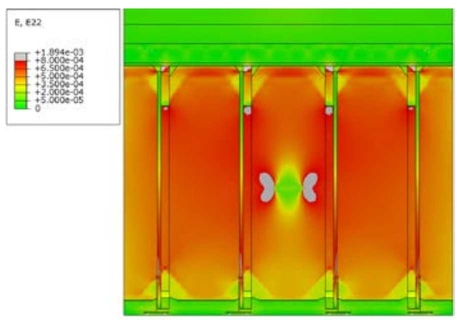

Figure 2. Strain field in vertical direction on FEM with a crack positioned in the center of the central skin bay.

The algorithm structure

Artificial Neural Networks have been selected as the most appropriate tool for the diagnosis, mainly because of their ability to “reason” on the basis of the experience created during the training phase [11]. This basic knowledge can be provided through finite element simulations, thus reducing the cost of the design phase. Different ANN structures have to be used according to the required task. Three types of ANNs have been trained in order to solve the Anomaly Detection, the Localization and the Quantification stages, respectively. The first layer, namely Anomaly Detection, receives the strain map at predefined positions and returns a value ranging from zero to one. It is a classic example of pattern recognition, which is entitled to distinguish between damaged and undamaged cases, thus to generate the alarm. After that, the function fitting algorithms have been trained to understand the physical functions that correlate the strain map to the position and the level of the damage. A standard feed-forward Neural Network trained by back propagation of errors has been adopted for each layer. More details about the ANN design are provided in Table 1.

Table 1. Parameters for Artificial Neural Network design.

Level	ANN type	Input layer	Output layer	Hidden layer Nr.	Hidden layer nodes	Training strategy
Anomaly Detection	Pattern Recognition	Strain map at sensor location	Damage index in [0,1] range (alarm threshold at 0.5)	1	15	Levenberg-Marquardt backpropagation
Localization	Function Fitting	Strain map at sensor location	[X,Y] position of crack center	1	15	Levenberg-Marquardt backpropagation
Quantification	Function Fitting	Strain map at sensor location	Crack length	1	15	Levenberg-Marquardt backpropagation

During ANN training, available data are usually randomly assigned to the three subsets, namely training, validation and testing (refer to [10] for details about ANN training procedure). This causes to obtain a different optimization every time the training function is activated, generating slightly different synapsis weights each time the ANN is trained. The robustness of the algorithm appears decreased if only one single ANN is used to evaluate the structural integrity. It has thus been decided to train 50 ANNs for each diagnostic level presented in Table 1, taking as output the average of the values obtained from all 50 ANNs.

The experimental test – Sensors and test rig

Four panels like the one reported in Figure 1 have been tested for dynamic fatigue crack propagation. A sinusoidal load with 12Hz frequency, 35kN peak load and load ratio (R) equal to 0.1 has been applied. 20 Fiber Bragg Grating sensors have been applied on each panel in order to perform the structural diagnosis (sensor network configuration has been optimized in [9]). FBG technology has been selected among the available technologies for strain sensing, having several advantages among which are light weight, low power consumption, immunity to electromagnetic interference, long lifetime and high sensitivity. Furthermore, they don’t require initial and in-service calibrations and are affected by a very low signal drop. From an economic point of view, the cost of using the FBGs is being reduced because of their extensive use in industry. Moreover, the multiplexing option, or the ability to photo-write multiple FBGs within a single optical fibre (the allowed number is strictly dependent on the maximum strain to be measured) is becoming particularly attractive for smart sensor network design. This technology allows reducing the logistic impact due to the installation of many sensors for large area scanning.

The same damage configuration has been studied in all the tests, that is to say a crack in the center of the central skin bay, like visible inside Figure 1. The damage has been artificially initiated in order to control the position and to study the repeatability of the test too. The signals coming from the 20 sensors have been acquired, normalized [10] and processed with the ANN structure introduced above, during crack propagation. Relative results are reported in Part II of the present paper.

PART II: VALIDATION OF THE FEM-BASED DIAGNOSTIC UNIT

The FEM trained algorithm structure has been tested before with FEM simulated crack propagations, nucleating from the positions indicated inside Figure 3. Then 4 real dynamic fatigue crack propagation tests have been executed in order to appreciate the reliability of the algorithm performance evaluation made with only FEM calculations. Concerning the FEM performance evaluation of the algorithm, the output of each diagnostic layer (crack detection, quantification and localization) is provided as a distribution due to the parallel running of 50 ANNs for each position in Figure 3. The 95% σ-band of the distribution is reported in Figures 4, 5 and 6, respectively referring to the anomaly detection, damage quantification and localization tests. The compliance of algorithm performance in laboratory environment with the predicted capabilities gained with FEM simulations can be appreciated in the same figures.

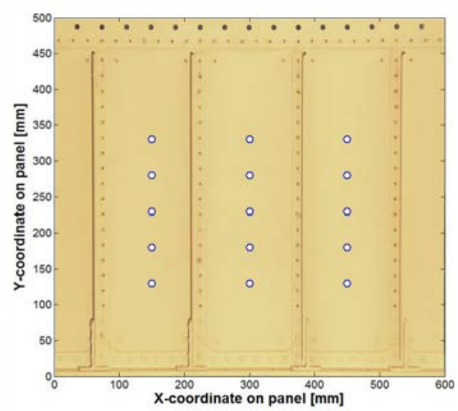

Figure 3. crack center positions over the panel used to test the diagnostic algorithm performances (with FEM simulated crack propagation).

Concerning the anomaly detection algorithm, it is clear in Figure 4 that the system classifies as undamaged a case with crack shorter than 40mm. After this threshold, the ANN output starts increasing, being the damage effect over the measured strain field more effective. It is also clear that the structure is classifiable as damaged when the crack exceeds 80mm. The 95% σ-band inside the 40mm – 80mm range is wider, being the ANN sensitivity particularly high inside that range. It is important to notice that the ANN behavior registered during the four real test cases is absolutely in compliance with the 95% σ-band FEM prediction. The irregularity manifested for case 2 is due to a sudden change in environmental temperature (test 2 has been executed without temperature compensator).

Focusing on damage quantification, the 95% σ-band reported in Figure 5 indicates that the algorithm reliability should increase while moving toward longer cracks, with higher and well defined effects over the measured strain field. Moreover, the confidence boundaries of the algorithm output (evaluated with FEM simulations) appear to be centered on the target crack length, apart from the case when cracks shorter than 20mm – 30mm are going to be measured. The effect of shorter cracks over the strain field is lower than the noise level, considering with noise any uncertainty inside the diagnostic system. Again, it can be noticed how the evaluation of the diagnostic system behavior with FEM simulations appears to be reliable for the appreciation of real algorithm performances. In particular, neglecting the system behavior for cracks shorter than 30mm, the quantification output for real tests falls inside the 95% σ-band of FEM distributions for the majority of cases.

Finally, some considerations about crack localization capabilities can be made referring to Figure 6, where the distance of the estimated position from the target one is plotted as a function of crack length. The first thing to be discussed is the reduction of the 95% σ-band while moving toward longer cracks. This means that the ANN estimation of crack position converges toward the right location while the damage becomes more effective over the strain field. This behavior is not reflected in the 4 experimental tests, probably due to the fact that the same damage with the same crack center position has been tested in all the four cases. On the other hand, FEM distributions are obtained with simulated crack propagation tests starting from the crack center positions indicated in Figure 3 and using 50 ANN in parallel trained with different randomly sampled damage databases. The algorithm performance for localization during tests is well described through FEM simulation, at least up to 70mm of crack length. Over this threshold, no general improvements have been recorded in real tests, in contrast with the FEM based prediction.

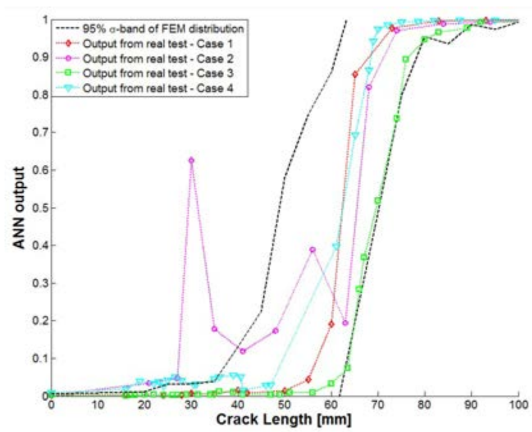

Figure 4. Anomaly detection output as a function of crack length (Real tests performance evaluation). The 95% σ-band predicted with FEM is also provided as a term of comparison.

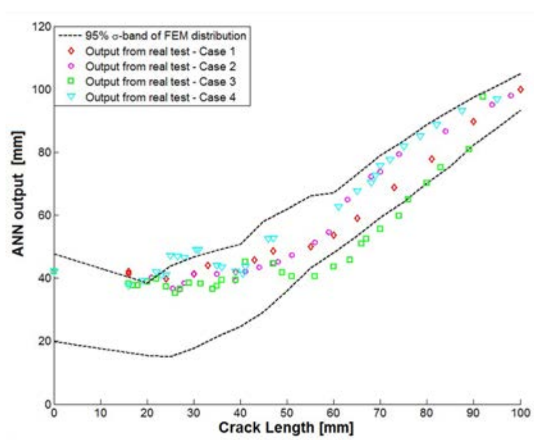

Figure 5. Damage quantification output as a function of crack length (Real tests performance evaluation). The 95% σ-band predicted with FEM is also provided as a term of comparison.

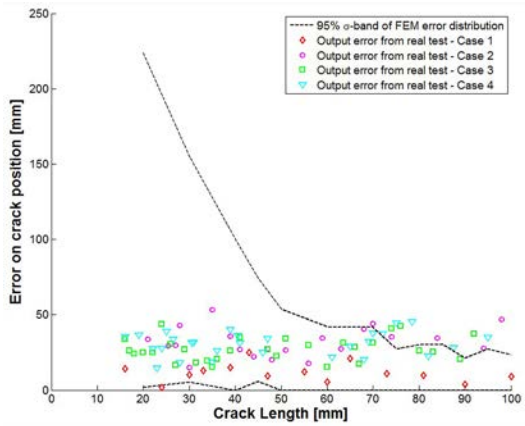

Figure 6. Error on crack position estimation as a function of crack length (Real tests performance evaluation). The 95% σ-band predicted with FEM is also provided as a term of comparison.

CONCLUSIONS

A FEM based methodology for fatigue damage detection, localization and quantification has been presented inside this paper. In particular, FEM has been used to train an Artificial Neural Network structure in recognizing damage characteristics. Moreover, FEM simulations have also been used to test the algorithm structure with different damages thus coming to an estimation of the algorithm performances. A test campaign consisted in 4 dynamic fatigue crack propagation tests and has been used to validate the performances estimated with pure FEM simulations in terms of:

- Minimum detectable crack length
- Uncertainty in crack length inference
- Error in crack position inference

It has been demonstrated that it is possible to use FEM for a preliminary estimation of diagnostic system performances, thus validating the methodology for a typical aerospace panel constituted by a skin, stiffened through some riveted stringers.

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