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Sensor Integration and Data Exploration of Structural Health Monitoring Network integrated on an Unmanned Aerial Vehicle (UAV)

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Abstract
Unmanned Aerial Vehicles (UAVs) require little human control while flying. Currently, UAV operations require time expensive maintenance due to the lack of sensing mechanisms to detect structural problems during the UAV operation. This paper presents the design and implementation of an SHM system applied to the rear fuselage of MILANO UAV by the use of FOSs and PZTs. The application of ANN for data processing will be discussed and validated with measurements on a real structure and numerical models. An SHM solution based on LSTM network will be proposed for an accurate real time damage detection with FBG sensing network.

1. Introduction

Damage is a local change in the material's properties or at the structure boundaries that degrades structural performance.[1] This aspect cannot be directly measured, so damage detection requires the measurement of a physical parameter affected by damage presence such natural frequencies. Although the changes induced by damage appearance in the strain field are obvious (intense in the local field, and smaller in the global strain map), damage detection and location by a sparse sensor strain network requires a damage detection algorithm which provide and accurate detection of damage presence, location and quantification[3] .
Among the strain sensors, FOS sensors are very attractive as sensors for SHM applications on aerospace composite structures, because optical fibers are very small size, low weight and multiplexing capabilities (several sensors on the same optical fibre). Additionally, it can be embedded within the composite material during manufacturing. Other benefits of FOS are EMI/RFI immunity, long term stability, wide temperature range and very long cabling if needed because of the low attenuation.
This paper deals with damage detection using two different types of FOS sensor networks: An FBG sparse sensor network with on flight measurement capabilities and a dense distributed sensor network based on Rayleigh scattering, with a higher number of sensors but only suitable for on ground measurements. The concepts are demonstrated and validated on the fuselage of a large unmanned aircraft structure.

1.1 SHM methods based on strain measurements

Strain measurements are very popular for damage detection strategies. Due to the limited spatial influence of the changes induced in the strain field, several applications are based on position the sensor in the expected damage area, like the bonding line between the stringer and the skin on composite structures. In the case of distributed sensing networks, the high number of the sensor network provides the capability of measuring large areas. Although the high maturity of strain sensors, a key issue to determine the damage straight from strain measurements is to compensate the

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unknown influence of external loads and temperature on the strain field. This, together with the limited sensing area, are currently the major limitations to implement this technique on field applications.

Strain sensors are commonly use on vibration-based methods, which inherently have the advantage of a global survey of the whole structure, and the limitation that damage needs to be large enough to modify the modal shapes.[4] Other widespread algorithms are Principal Component Analysis (PCA). PCA is a simple and nonparametric method of extracting relevant information directly from strain data. It is done by reducing a complex dataset to a lower dimension, revealing some hidden structure/patterns or abnormal data. This is done by converting a set of data of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. In the same line, Support Vector Machines (SVMs) classification learning is a powerful paradigm to investigate inverse input-output relationship of a specific problem according to some available and representative dataset.

Due to its intrinsic nature, machine learning algorithms match perfectly with SHM applications, as they are design to find natural patterns in data that generate insight. Different applications can be found in the bibliography. Initially, Artificial Neural Network (ANN) was used to determine changes on vibration or in time series.[5] However, new developments on ANN provide the capability to detect a based on the strain field sensitivity to damage presence. Fatigue cracks and the distortion of the FBG spectrum have been previously studied.

2. INESSASE - Milano RPA SHM system description

The Milano is a remotely piloted aircraft (RPA), designed and built by INTA (Spanish Aerospace Research Centre), with a service weight of 900 kg, and up to 20 hours autonomy and a set of payloads up to 150 kg. The whole structure is done with CFRP materials and it has a length of 8,2 meters, and a wingspan of 12,5 meters. A picture of Milano can be seen in Figure 1.

Figure 1: General view of Milano RPA

The research project INESASSE (Sensor Integration and data Exploitation of SHM Integrated on an UAV), as a collaboration among the INTA and the UPM, has the objective of developing an SHM system for Milano RPA using FBG in flight strain measurement. Milano is equipped with an FBG four channels interrogator (Smart Scan Aero Mini from Smart Fibers Company). The two structures under study are the wing and the rear fuselage. The CFRP elements (skins, stringers, stiffeners and bulkheads) are in general bonded using a two-component structural adhesive. For this kind of unmanned vehicles, which must work under very rugged conditions; small energy impacts during takeoff and landings, hard landings overstress and overacelerations are the most critical events during the operation. These events could promote delaminations and debondings of structural elements.

As debonding damages can compromise the structural integrity and operation, project has focus in identify, locate and quantify this type of damage. Up to four different debonding areas have been identified as critical. These zones are located between the frame and the skin of three of the four bulkheads and in the lateral joint between the lower and the upper rear fuselage skin, as shown in Figure 2.

Up to 20 FBG strain sensors (5 per each FBG measurement channel) were located in the expected maximum strain change induced by the combinate damage. One temperature sensor has been introduced in each sensor line in order to perform temperature compensation during flight operations.

The measured strain data will be compared with reference strain values of the pristine structure. The physical principle for the damage detection is the load path change due to the presence of a structural damage. The load re-distributes inside the structure, if any of their elements changes their stiffness, due to the reduction of its load bearing area by, as for instance debonding of structural elements. This re-distribution of the load results in differences of the strain distribution inside the structure and can be detected by the integrated strain sensor network. Small damages, such cracks or delamination, can not be detected if the changes induced have not global influence.

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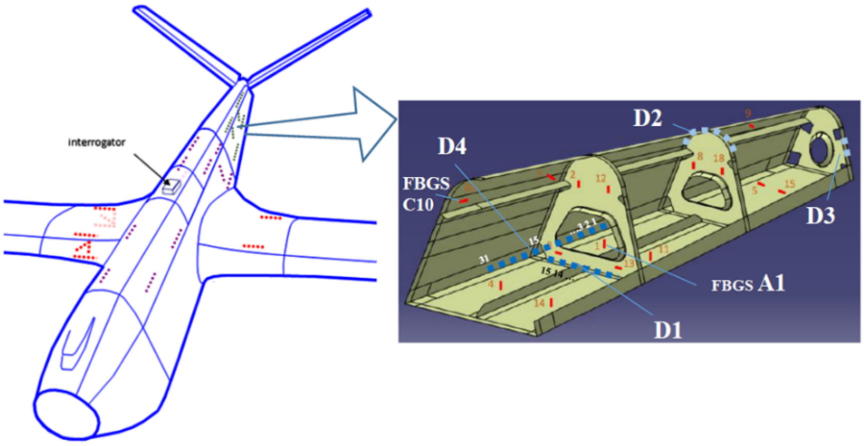

Figure 2: General scheme of MILANO (left) and a detailed view of the rear fuselage (right)

3. Experimental validation

The rear fuselage of Milano is a 2,5 meters long structural part, full made of CFRP and composed by two stiffened skins and four ribs, joined by adhesives. The specimen was attached to the test rig using the same fittings they are used to attach the rear fuselage to the forefront fuselage and tail structure, in order to kept as in the original design. These fittings are used during the tests to provide known boundary conditions and test the rear structure in cantilever condition. Flexion and torsion load cases are introduced in the opposite side with a pair of hydraulic actuators of 3kN, each, like it is expected in operation conditions (up to 4kN in flexion and 1kNm in torsion). FBG Sensor are attached inside the structure, as in real flight element. Additionally, a distributed sensor network is set up by a single optical fibre with a layout of seven longitudinal sensor lines, four in the lower skin and three in the upper skin, symmetrically distributed on the structure, attached in the surface. Strain was measured at different load steps during all the damage states. A general view of the test set up can be observed in Figure 3.

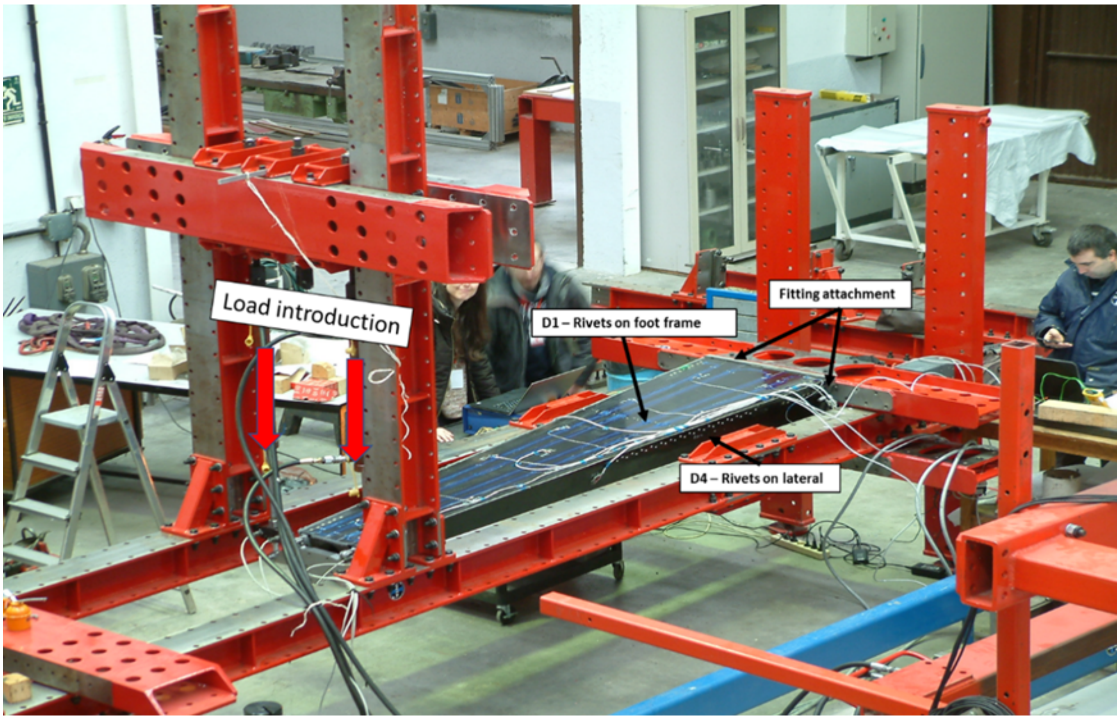

Figure 3: Testing rig loaded with two hydraulic actuator and fixed as cantilever in its central fuselage attachments

For this test, the four critical damage areas identified are not bonded but riveted, so that, the structural continuity is

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guaranteed but offering the possibility to introduce damage by removing rivets step by step. Progressive damages are introduced in four areas, simulating the debonding of the different components of the structure by removing the rivets gradually. Damage 1 to 3 simulate the debonding between the skin and the frames, and Damage 4 simulate the debonding between the upper and lower fuselage skin. In Figure 4 the different damage cases under study can be seen.

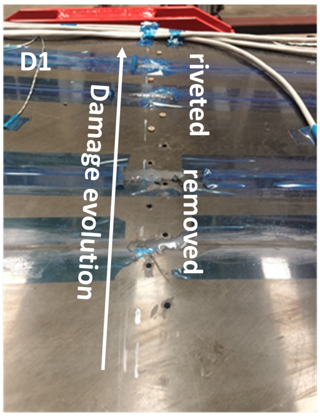

Figure 4: Detail of the removed rivets from the lower skin and the second frame(Damage D1) and between the upper skin and the lower skin (Damage D4) with the rivets partially removed

4. Experimental results and discussion

4.1 Principal Component Analysis (PCA)

PCA is a widely use non-parametric method of extracting information from large data sets. Is a classical multivariate analysis procedure to reduce a complex data set to a lower dimension and reveal some hidden structure/pattern. The original data are reexpressed in a new orthogonal basis where the data are arranged along directions of maximal variance and minimal redundancy, called principal components. Damage indicator for this technique is the Q-index and the detection capability has been proven at different damage states using FBG strain with the full loaded structure. Although Q-index is a powerful damage indicator, capable of detecting damage increments, it cannot be used to determine damage location or accurate damage evolution. However, due to its easy implementation and fast processing, it is a very widespread SHM analysis method. A detailed discussion was formerly presented at APWSHM 2018[2] and will not be repeated here.

4.2 Artificial Neural Network (ANN)

Machine learning algorithms use computational methods to “learn” information directly from data without relying on a predetermined equation as a model. The algorithms adaptively improve their performance as the number of samples available for learning increases. In this case, the structural diagnosis is carried out by an ANN, proposed to solve a multiclass classification problem (each damage previously defined and undamaged state at different load levels). ANN has the capability to be trained on a database of FEM simulations relative to damaged and undamaged conditions, providing an accurate prediction and reducing the experimental costs associated with the development and optimization of SHM system.
For the distributed sensor network, the selected ANN is a feedforward backpropagation static architecture with 16 inputs (2 damage cases and the reference at 16 load steps, one hidden layer of 120 neurons, and 2 outputs, the damage indicator profiles at the two considered damage locations. The ANN output is an indicator of damage for a predefined set of trained situations, providing a strain profile of the different training damage cases, in this case damage 1. By the use of this methodology, damage map is independent of the load state. Nevertheless, the main limitation of this technique is the processing time and system cost and measurement acquisition time, unable for in flight measurements.
For the FBG network, Long Short-Term Memory (LSTM) networks has been studied. LSTM are a branch of Recurrent Neural Networks (RNN), capable of learning long-term dependencies between steps of sequence data. The network is trained by iteratively modifying the strengths of the connections so that given inputs map to the correct response. Figure 6 illustrates the architecture of a simple LSTM network for classification. The network starts with a sequence input

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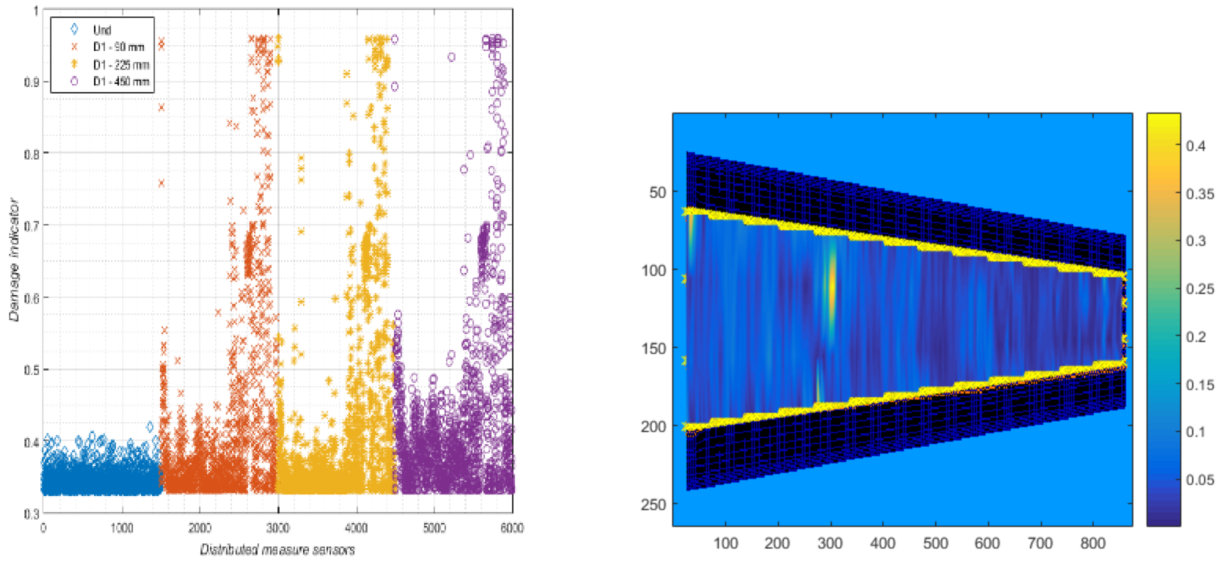

Figure 5: ANN Damage indicators for distributed sensing network for increasing D1 at different load states (left) and damage map using damage indicators (right)

layer followed by an LSTM layer. To predict class labels, the network ends with a fully connected layer, a SoftMax layer, and a classification output layer.

Figure 6: LSTM Network Architecture

LSTM network has been initially developed, trained and validated with FEM data, to which it has been added a gaussian noise with an amplitude of 5 microstrains. Five different states have been implemented: undamage (Und), damages 1, 2, 4 and combination of full 1 and progressive 4 (D1, ..., D14). Training has been done using up to 400 measures at different load states and validating on 80 at different load levels. An accuracy of 96.3% has been achieved using this methodology. The same algorithm has been tested on 32 real experimental strain patterns (the tests with higher load), thus verifying the capability of the algorithm trained with a FEM for anomaly detection, damage assessment and localization on the correspondent real complex structure. In this case, accuracy has been reduced up to 81.3%. By the last, the same LSTM architecture has been trained using 520 experimental data sets at different load states and validated with 104 experiments, achieving an accuracy of 96.2%.

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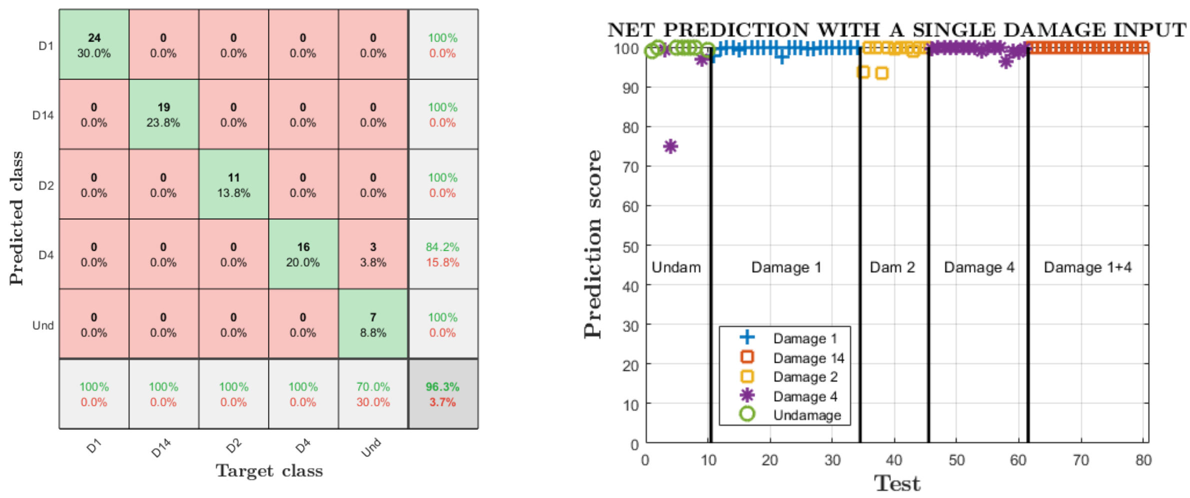
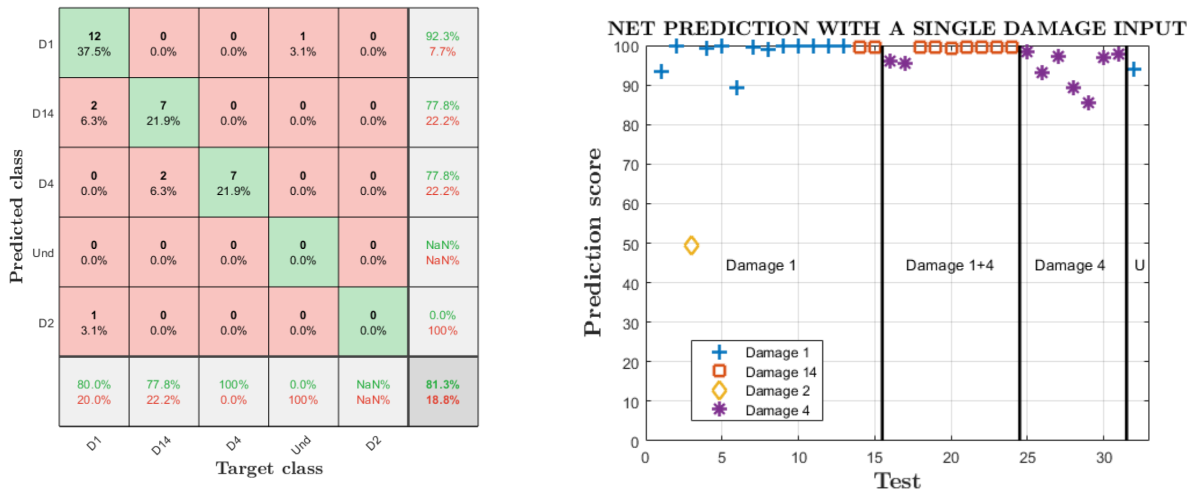
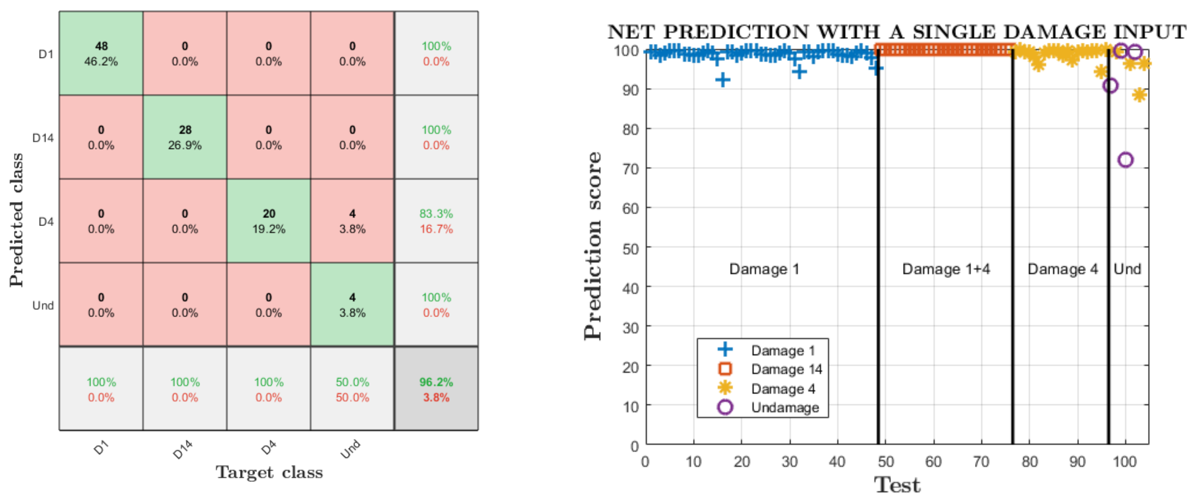


(a) Validation confusion matrix trained and validated with FEM



(b) Validation confusion matrix trained with FEM and validated with experimental data



(c) Validation confusion matrix and resumed prediction score with different training and validating data

Figure 7: Validation confusion matrix and resumed prediction score with different training and validating data

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5. Conclusions

The benefits of the SHM approach for UAV inspections without disassembly address to minimising costs, improving reliability, and maximising availability of aircraft. Based on previous results, it can be concluded:

- Fiber optics are excellent strain sensors, but not 'damage sensors'.
- PCA provides an index to calculate the damage occurrence. However, this technique can not calculate the damage location or to assess damage size.
- ANN requires a previous training and are more difficult to use and compute; nevertheless ANN could provide not only the damage assessment, but also could provide a detail localisation of the damage area that can be presented as a damage map.
- LSTM networks provides a high accuracy and performance when they are trained with the same data that they were validated. However, when the ANN trained with FEM data network is validated with the real data the accuracy decreased. This can be explined with by the discrepancy between the FEM and the real structure. Nevertheless the high accuracy in the damage detection demonstrate the high potential of this technique, although the uncertainty in the algorithm training process due to a small number of training data set requires the implementation of an optimisation process while net training in order to achive an acceptable accuracy.

6. Acknowledgments

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