Study of sensitivity for strain-based structural health monitoring

A Herrera-Iriarte¹, J Alvarez-Montoya¹ and J Sierra-Pérez¹

¹Grupo de Investigación en Ingeniería Aeroespacial, Universidad Pontificia Bolivariana, Medellín, Circular 1 # 70-01, Colombia

Abstract. One of the available methodologies for structural health monitoring (SHM) is based on strain field pattern recognition where, through the use of sensors capable of measuring strain on discrete points and machine learning techniques, it is possible to detect a damage event. In this study, strain data from fiber optic sensors (FOS), in particular fiber Bragg gratings (FBG), acquired through two experiments are used: an aluminum beam with 32 FBGs and CFRP beam provided with 20 FBGs, which serves as the main wing’s structure of an unmanned aerial vehicle (UAV). Both structures were subjected to dynamic loading for a pristine condition and later, for artificially damaged conditions. In the experiments presented in this paper the beams were provided with different amounts of sensors which were removed one by one in order to analyze the sensitivity of the damage detection methodology based on PCA to a change in the number of sensors. The results demonstrated that there are few sensors that contribute mostly to the methodology’s performance, these sensors are validated to be the ones located near the analyzed damage condition. Therefore, this study is the first step into the development of methodologies of damage localization using strains.

1. Introduction

Monitoring techniques are important on the reliability of several industries such as aerospace, civil construction, nuclear and automotive. Since any real system or structure wear out, it is paramount to identify how and when a catastrophic failure will occur, guaranteeing the serviceability of the system over time and, therefore, avoiding human and economic losses. Having as example an airline, structural maintenance represents 33% of the total maintenance cost, at the same time maintenance is around 20% of total costs of an airline, therefore, it is important to find a solution that reduces costs while not affecting reliability [1].

Structural health monitoring (SHM) refers to the implementation of a damage detection strategy through a network of sensors in order to monitor and extract damage-sensitive measurements to determine the integrity of a structure or a system over time [2]. This approach allows the shift from a schedule-driven maintenance regime to a condition-based maintenance (CBM) [3]. That is why, nowadays, it has raised the interest among industrials and academics in SHM due to the most quantity of benefits that this could bring to traditional monitoring techniques such as non-destructive testing (NDT). These benefits include real-time damage detection that could lead to a reduction of safety factors for composite materials (in order to design more efficient and lighter structures), damage severity and location assessment and maintenance cost and time reduction for aerospace applications by replacing traditional NDT which consumes a lot of resources and time.
Among the available methods for performing SHM, one of the most promising ones is strain-based SHM using fiber optic sensors (FOS). These strain sensors have the capability of being embedded into the material in the manufacturing process without being invasive and degrade the performance of the system. Once sensor information is obtained, data processing has to be carried out in order to decision-making, for this, some of the most successful methods are the application of pattern recognition and machine learning algorithms, and one of the most used machine learning techniques for this purposes is principal component analysis (PCA) [4].

PCA consists of a statistical method in which a data with several dimensions can be reduced to a desirable number of components that has the characteristic of showing the highest possible variability with the established components. SHM systems usually require a large number of sensors acquiring data over a large period, therefore, it is necessary to use dimensionality reduction techniques in order to ease the processing [2].

The authors have been working on the use of PCA to perform damage detection from discrete strain measurements acquired by fiber Bragg gratings (FBGs), a type of FOS. Such approaches have demonstrated suitable results in several experiments such as an aluminum beam subjected to dynamic loading [4] and an unmanned aerial vehicle (UAV) composite beam under real operational conditions [5]. Although several experiments have been performed by using strain data in conjunction with PCA, there are no studies that quantify changes on damage indexes as a function of the number of used sensors. One important question when designing such SHM systems, is the quantity of sensors required in order to have an appropriate sensitivity. In this study, data from two experiments (aluminum beam and UAV composite beam) were used in order to perform a sensitivity analysis with a variable number of sensors. The analysis is based on removing specific sensor data and analyzing whether left sensors can detect damages. The aim is to provide tools that allow designers to decide the adequate number of sensors in a desired application in order to design SHM systems with higher cost-benefit ratios. In addition, this study can provide useful information for damage localization since near-damage sensors are supposed to contribute more to the damage detection capability [6].

2. Background

There are many ways of performing SHM aside strain-based analysis, a few are discussed below. One popular method referred to vibration-based SHM is acoustic emissions in which sensors are special “microphones” that “listen” the structure and predict with this noise if a failure is about to occur. This method has the disadvantage of having a lot of noise on their measurements and required more robust equipment compared with strain-based analysis using FOS. Another used method is acceleration-based SHM in which a lot of accelerometers are installed around a structure, this method is an alternative to measure strains indirectly. Temperature is another possible variable to measure in order to detect damages, but this method does not have enough sensitivity for detecting small damages and it is mostly used for detecting humidity into materials or big scale damages [7].

PCA as a machine learning method is used not only in SHM applications, it has a lot of additional applications. It is used, in general, for image identification (facial recognition and image classification as well), fingerprint scanning, recently for sound recognition [8] and the studies in medical sciences for heart rate monitoring [9]. As mentioned before, PCA tents to reduce components of a multidimensional array with the most possible quantity of information in the components obtained. It is important to identify the final dimension of the matrix when PCA is applied, for example, if initially there is a matrix of 4000 x 20, it means that there are 4000 measures (or samples) and 20 sensors (or features), with a PCA algorithm it is intended to obtain a 4000 x 3 matrix, it means that the initial 4000 x 20 matrix is projected from a 20-dimensional space to a 3-dimensional space. For this, the following equations are used:

\[
\text{coeff} = \lambda(\text{cov}(A)) , \tag{1}
\]

\[
\text{score} = A \times \text{coeff} , \tag{2}
\]
where, \( A \) is the initial matrix and \( score \) the resultant matrix after PCA is applied. In equation (1) projection matrix \( coeff \) are the eigenvectors of covariance [8]. For all experiments the data is divided into a baseline matrix (a healthy condition matrix) and a D0 matrix (that is a undamaged data matrix used for validation). Finally, D1, D2, D3 ... DN, are the data matrices for different damage conditions. Once obtained the PCA reduction matrix, it proceeds to classify as damage or no damage. This is done with help of \( Q \) index which is calculated using following equations:

\[
\bar{X} = score \times coeff^T, \\
E = A - \bar{X}, \\
Q = \sqrt{E \times E^T},
\]

(3)\n(4)\n(5)

Where \( Q \) index is a vector equal to measures number [4]. In machine learning techniques; it is common to perform receiving operating characteristic (ROC) analysis in order to determine the performance of a classifier. Within this analysis it is important to define several metrics such as true positive (TP), data which belong to a detected damage that is a real damage, true negative (TN), when there is no damage detected and the structure is undamaged, false positive (FP), when there is no a damage and algorithm detect damage and false negative (FN) when a damage exists and the algorithm does not detect it.

\( F1 \) score values determine the accuracy of a classifier, it takes a value between 0 and 1 being 0 the worst and 1 the better case. It is commonly used due to it allows performance comparison combining the above discussed metrics in one.

\[
F1 = \frac{2 \times TP}{2 \times TP + FP + FN}
\]

(6)

3. Experimental setup

As mentioned before, two experimental data sets were used, one from an aluminum beam submitted to cyclic bending loads and the other from the SMARP UAV structure made of CFRP.

The aluminum beam structure experiment was performed under a controlled environment obtaining a true positive true rate of 100% and a false positive rate of 1.28% [4]. The beam had a rectangular cross section of 20 mm x 40 mm and a total length of 1200 mm with 32 FBG sensors bonded to its surface. Cyclic bending loads were applied into a cantilevered beam by attaching it to an AC motor provided with a connecting rod. A total of six artificial damages were induced by drilling holes which produced a small local change in stiffness. In figure 1, a depiction of the damage locations is presented, where the damage selected preliminary for the study is highlighted in red (D5). For a detailed description of the experiment see [4].

The SMARP UAV beam experiment was performed using 20 FBG sensors embedded in the SMARP UAV structure. Real operation tests (flights) were carried out obtaining a true positive rate of 99.7% and a false negative rate of 0.3% [5].

The UAV flight data was sent in real time to a ground station using 2.4GHz WLAN wireless system, during the tests a lot maneuvers were performed, varying roll, pitch and yaw angles, speed, vertical speed. The simulated damages in the structure were performed by bonding plates of a stiffer material on certain points of the structure. In figure 2, a depiction of the damage selected for the study is detailed in conjunction with the near sensor locations. For a detailed description of the experiment see [5].

4. Results and discussion

Results of \( Q \) index for both experiments are presented in figures 3 and 4.
Figure 1. Damage localization for aluminum beam [4].

Figure 2. Damage localization for CFRP beam [5].

As can be seen in figure 3a and figure 4a damage cases are over the thresholds, it means that damages are detected, however, for figure 3b and figure 4b damages are under thresholds so there are no damages detected. It can be appreciated that by reducing the number of sensors the capability of the methodology of detecting damages is seriously affected. Based on such figures, the $F_1$ score is calculated for each experiment and for different number of sensors (see figures 5a and 5b). It is important to highlight that sensors were removed from nearer to farther sensor from damage. It can be seen that in both cases there is a number of sensors from which there is not considerable changes in the $F_1$ score, which means that said sensors are not contributing considerably in the damage detection process.

Figure 3a. $Q$ index for 20 operating sensors, CFRP experiment.

Figure 3b. $Q$ index for 3 operating sensors, CFRP experiment.

Figure 4a. $Q$ index for 31 operating sensors, aluminum beam experiment.

Figure 4b. $Q$ index for 4 operating sensors, aluminum experiment.
Figure 5a. $F_1$ score vs sensors number for aluminum beam.

Figure 5b. $F_1$ score vs number of sensors for CFRP beam.

5. Conclusions
For $F_1$ scores plot it can be observed that when sensors number increases there is a point in which $F_1$ score does not increase significantly, this point indicates an ideal number of sensors that could be installed in order to have a balance in cost and sensitivity. For the CFRP beam case when ten sensors are operative there is a 0.99 rate for $F_1$ score what indicates an acceptable reliability and for the case of the aluminum beam, the score after ten sensors removed is 0.99. For both cases, the $F_1$ score does not increases significantly when there are more than ten sensors, it means that, for these two damage examples and experiments, a damage can be detected for multiple sensors especially those that are located near the damage, this having into account that sensors were removed from nearer to farther from the damage location. This represents valuable information toward damage localization using strain data and machine learning techniques since the location of the damage can be delimited to the zone where the sensors with the most considerable contributions to the $F_1$ score are presented the contribution of the sensors to the performance of the methodology.

6. References
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