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Decision trees-based methods for the identification of damages in strongly damped plates for aerospace applications

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Abstract. Damage identification and localization is fundamental in industrial engineering, since it helps perform corrective actions in time to reduce as much as possible system downtime, operational costs, perform quick maintenance and avoid failure. Recently, structural health monitoring has found in machine learning an extremely useful tool, making the monitoring of complex systems more manageable. In this work, composite plates manufactured with the purpose of damping vibrations in aerospace structures are experimentally tested; the strong damping suddenly reduces the vibrations, leading to responses very similar to one another, without noticeable or structured differences between undamaged and damaged plates. To overcome this issue, machine learning methods are applied. Decision trees-based methods are chosen since they provide a combination of feature selection capabilities and robust classification performances. The used methods are decision trees themselves and two boosting methods: AdaBoost and RUSBoost. All three methods perform well in identifying damaged plates, the type (thickness damage and debonding) and sub-type of damage (thickness/debonding of types A and B).

Introduction

Damage is defined as an intrinsic change in geometrical or material characteristics of an engineering system that negatively affects its operational life, safety, reliability, and performance [1]. The detection, diagnosis, and prognosis of failure can be performed through Structural Health Monitoring (SHM). The most challenging step in SHM is damage detection, interpreted as the systematic and automatic process of finding the existence of a damage. As Yuan et al. [2] report, damage detection has been performed in SHM with two approaches up to now: physics-based and data-driven. The former becomes unreliable as the system complexity increases. Improvements in computational power and advances in information and sensing technologies allow monitoring of many parameters, which opens the path to data-driven approaches. As reported by Avci et al. [3], during the last decades, Machine Learning (ML) has been widely applied to SHM, with the objective of generating models mapping input patterns in measured sensor data to output targets for damage assessment.

This work is executed in the framework of IDEFISC (IDEntification de FISsures dans les Composites) project, aimed at the identification and quantification of damages in composite structures with the aid of machine learning methods. The test articles under investigation are composite plates consisting of three layers: a metallic, an elastomeric and a composite one, aiming to damp the vibrations in aerospace vehicles. Such strong damping leads to a sudden reduction of

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vibration amplitude, making the responses remarkably similar between healthy and damaged plates, impairing the damage identification task. The need of fast and reliable methods paves the way to the powerful classification capabilities of machine learning methods, exploited here to distinguish which plate is damaged and which not, but also to identify the types (reduction or debonding) and sub-types (changes in position) of damages.

Theoretical framework

Three machine learning methods are used in this work. The first method is decision trees. They have a flowchart-like structure, characterized by nodes, in which a test on an attribute is executed, and branches representing the outcome of the test [4]. Each split is executed to maximize the information gain, so that the most informative feature is used to determine the status of the sample. Decision trees are attractive models because of interpretability, they allow mixing feature types, and automatic selection of the optimal feature. However, they tend to overfit when trees are too deep. A typical approach to fight overfitting is to build a more robust model through ensemble methods: they combine several weak classifiers into a meta-classifier having better generalization performances than an individual classifier alone. There are different types of ensemble learning; the one used herein is AdaBoost (Adaptive Boosting), in which several decision trees are trained in series so that, at each iteration, the training examples are re-weighted to build a more robust classifier which learns from the errors of the previous classifier in the ensemble. The final prediction combines the outputs of all the weak learners and is taken by majority voting. A modification of AdaBoost is used as third method: RUSBoost (Random UnderSampling Boosting). It is very effective when the classes are not evenly distributed in the dataset. Instead of involving the entire training set (like AdaBoost), RUSBoost takes the basic unit for sampling equal to the number of members N in the class with the smaller number of instances in the training data.

Experimental tests and application of machine learning

The plates may present two types of purposely made damages: thickness damage, and debonding between the aluminum and elastomeric layers. In turn, each damage type appears in two sub-types, labeled A and B, in which size and location of the damages change. Eleven plates are tested, in total. Three plates are undamaged, while the remaining ones have one sub-type of damage.

Global vibration tests are executed on the plates to obtain their response in both the time and frequency domains. The test articles are clamped on the short side, they are excited with a 1.5 second sweep sine signal provided through an electrodynamic shaker on the aluminum part, ranging from 5 to 5000 Hz. Velocity measurements are performed with a Polytec LDV (Laser Doppler Vibrometer) on the composite part in 187 points. The frequency response of one point is displayed in Fig. 1: there are no noticeable differences among the several damage conditions.

The dataset is made of 10 plates and 25 features, extracted from both time and frequency measurements, such as summary statistics, frequency centroid, roll-off frequency, time of flight, etc. The features are estimated for all the measured points, thus the entire training set contains 1870 observations. Three identification tasks are performed: damage identification, damage type identification, and damage sub-type identification. Thus, a label is assigned to each observation, corresponding to the status of the plate. The generalization capabilities of the machine learning methods are checked considering one plate at time for testing. Hence, all the observations of one plate are extracted from the dataset to generate the test set, and all the remaining observations, belonging to all the other plates, are shuffled and constitute the training set. This procedure is performed several times, one for each plate.

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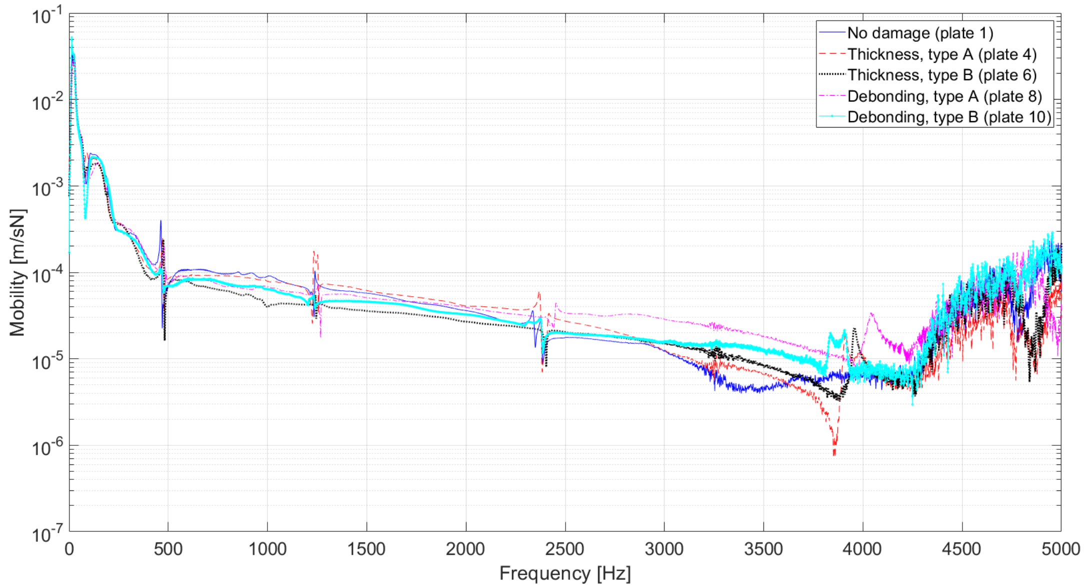

Figure 1 - Mobility of the tested plates.

For sake of brevity, the results of all the tasks are summarized in Tables 1-3, where the acronyms DT, AB, and RUSB stand for Decision Trees, AdaBoost, and RUSBoost, respectively. Plate 1, without damage, is used as baseline for the estimation of those features requiring the comparison of the test plate with an undamaged plate, thus it cannot be used for machine learning. The test plates are reported along the rows, the columns refer to the methods; each cell provides the proportion of correctly classified measurements with respect to the total number of measurements performed for each plate. The results show that not all the labels are correctly predicted: Plate 8 always provide misclassifications, and the ratio of wrong predictions increases as the complexity of the task increases. However, the overall performance capabilities are very good, since the majority of the measurements are associated with a correct prediction of the status of the plates.

Plate ID	DT	AB	RUSB
Plate 2	187/187	187/187	187/187
Plate 3	187/187	0/187	187/187
Plate 4	187/187	187/187	187/187
Plate 5	187/187	187/187	187/187
Plate 6	187/187	187/187	187/187
Plate 7	187/187	187/187	187/187
Plate 8	0/187	0/187	0/187
Plate 9	187/187	187/187	187/187
Plate 10	187/187	187/187	187/187
Plate 11	187/187	187/187	187/187

Table 1 - Classification performances of DTs, AB, and RUSB, undamaged-damaged classification task.

Plate ID	DT	AB	RUSB
Plate 2	187/187	187/187	187/187
Plate 3	187/187	0/187	187/187
Plate 4	187/187	187/187	187/187
Plate 5	187/187	187/187	187/187
Plate 6	187/187	187/187	187/187
Plate 7	187/187	187/187	187/187
Plate 8	0/187	0/187	0/187
Plate 9	187/187	187/187	187/187
Plate 10	187/187	0/187	187/187
Plate 11	0/187	187/187	187/187

Table 2 - Classification performances of DTs, AB, and RUSB, damage type identification task.

Table 3 - Classification performances of DTs, AB, and RUSB, damage subtype identification task.

Plate ID	DT	AB	RUSB
Plate 2	187/187	187/187	187/187
Plate 3	187/187	0/187	187/187
Plate 4	187/187	187/187	187/187
Plate 5	187/187	187/187	187/187
Plate 6	187/187	187/187	187/187
Plate 7	187/187	187/187	187/187
Plate 8	0/187	0/187	0/187
Plate 9	187/187	187/187	187/187
Plate 10	187/187	0/187	187/187
Plate 11	0/187	0/187	187/187

Conclusions

This work's main aim is to classify the health status of plates characterized by strong damping. Such a damping explains the responses of experimental vibration tests, remarkably similar among plates with and without damages. However, what is undistinguishable for the human eye provides valuable information for machine learning techniques. In fact, the application of three methods, namely decision trees, AdaBoost, and RUSBoost, proves that data-driven methods have excellent classification capabilities: the presence of damage itself, damage type and sub-type are correctly predicted with high accuracy. This opens the way to new, more advanced types of tasks, such as identification of smaller damages, as well as their localization.

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