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Data-driven deep neural network for structural damage detection in composite solar arrays on flexible spacecraft

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Abstract. A data-driven approach based on Deep Neural Network (DNN) techniques is here proposed for Structural Health Monitoring of large in-orbit flexible systems. Damage scenarios are generated via a Finite Element commercial code to train and test the machine learning model, by considering equivalent properties of the composite material of the solar panels. The fully coupled 3D equations for the flexible spacecraft are integrated to test typical profiles of attitude manoeuvres in case of different damages. The DNN model is trained using sensor-measured time series responses, with each response associated with the label of the corresponding damage scenario, and tested via k-folding approach. This methodology offers a promising approach to detect structural damage in solar arrays on spacecraft using machine learning techniques.

Introduction

With the increasing use of composite materials in solar arrays on modern spacecraft, structural damages during the operational life have become a significant concern. Such events often lead to modifications of the control/structure interaction dynamics, thus posing an issue for the implemented system controller. Detecting failures in flexible structures can however be challenging: local damages may not cause significant changes in the global dynamics of the satellites to be detected by on-board sensors. Therefore, a set of sensors at structural level is beneficial to identify promptly the location and the entity of the damages.

As far as current state-of-the-art solutions for damage identification are concerned, there are mostly two adopted philosophies: physics-based and data-driven methods [1-3]. The purpose of this study is to propose a Deep Learning methodology with multi-classification damage capabilities, with respect to the research proposed by the authors' previous work [4-5]. Indeed, the present study aims at proposing an architecture and guidelines for performing SHM of space structured based on LSTM-NNs. A challenging study case in terms of impact of failures on the global spacecraft dynamics is selected, and a more complex problem in terms of higher dimensionality of the multi-class identification problem is addressed, giving information not only about the presence, but also the location of the damage. The structure and damage entity is implemented taking into account the equivalent properties and effects on a traditional composite space structure, in particular, an aluminum honeycomb.

The approach is carried out as follows. Firstly, the 3D mathematical model of a flexible spacecraft is implemented in a simulator for carrying out a wide set of in-orbit attitude maneuvers. Then, the spacecraft test case model is described, including the network of distributed sensors for the SHM and the damage configurations addressed herein. The implemented deep neural architecture is described, based on an LSTM variant. Finally, the main results about the performance of the trained classification network are discussed.

Bidirectional Long-Short Term Memory Network

The efficacy of Long Short-Term Memory (LSTM) models has been validated in various domains, notably within the area of time series prediction [6][7], as well as for both single-variable and

multi-variable time sequence classification tasks [8]. LSTMs are purposefully crafted to exploit long-range dependencies, enabling them to effectively address scenarios where the present time step is distant from correspondent information. By incorporating the capability to effectively process historical data within a single cell, Deep Neural Network (DNN) architectures can benefit by establishing connections across multiple LSTM layers.
Details about the structure of a LSTM network can be found in [8]. In this study, we use a multivariate deep classification model composed of an input layer, two stacked Bi-LSTM layers, including a dropout layer to address overfitting issues, a Softmax layer, and a final classification layer.

Spacecraft Dynamics and Damages
This section briefly introduces a representative case of a spacecraft equipped with two solar panels of 3 x 1 m (composed of two sub-panels each), designed using MSC Nastran FEM tool based on information available in literature about dimensions, mass and shape of the panels. The first three modes of the assembled spacecraft are illustrated in Fig.1. Since the size and mass constraints at launch require solar panels to be lightweight, while strong and stiff, a composite material – an aluminium honeycomb here specifically - is selected for each sub-panel. Moreover, to reduce the complexity of FE model, an equivalent model of the multi-layer composite structure is here considered as a single-layer panel. The equivalent thickness t_{eq}, and stiffness moduli E_{eq} and G_{eq}, obtained by solving the equations in available literature [9], are

$$t_{eq} = \sqrt{3h_c^2 + 6h_c t_f + 4t_f^2} \qquad E_{eq} = \left(2t_f E_f\right)/t_{eq} \qquad G_{eq} = \left(2t_f G_f\right)/t_{eq} \tag{1}$$

where t_f is the skins thickness, h_c is the height of honeycomb core, E_f and G_f skins moduli. The equivalent data for a 10mm sandwich panel are $t_{eq} = 0.0156m$, $E_{eq} = 90GPa$, $G_{eq} = 3.31GPa$.

At the same time, the Modal Strain Energy (MSE) - defined as the amount of elastic energy stored in a finite element - associated to the flexible appendages was computed. The related MSE map (see Fig. 2) is used to identify the locations of the elements whose change in mechanical properties could be more problematic for the global dynamics of the system. The objective is to avoid building a heavy set of data including damages all over the structure (also damages associated with low risk, i.e. inducing a negligible change in the modal properties of the satellite), potentially leading to an excessively high dimension multivariate classification problem. Instead, the approach proposed here is to discriminate a set of potential critical damages, to be identified via the deep learning architecture, based on MSE concentration.

In this research, damages are considered as resulting from space debris hits, causing a perforation in the structure. The dimension of damage is assumed as not exceeding 5cm x 5cm, which is a representative size for high velocity impacts for aluminium honeycomb [10]. Damages are simulated only on one solar panel. Hence, a set of three-axis accelerometers sensors are installed on one side. In particular, the position of the sensors is depicted in Fig. 3.

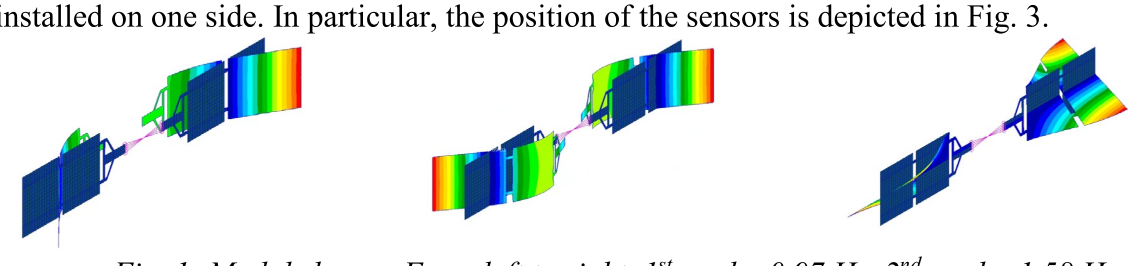


Fig. 1: Modal shapes. From left to right, 1st mode: 0.97 Hz, 2nd mode: 1.58 Hz, 3rd mode: 3.27 Hz

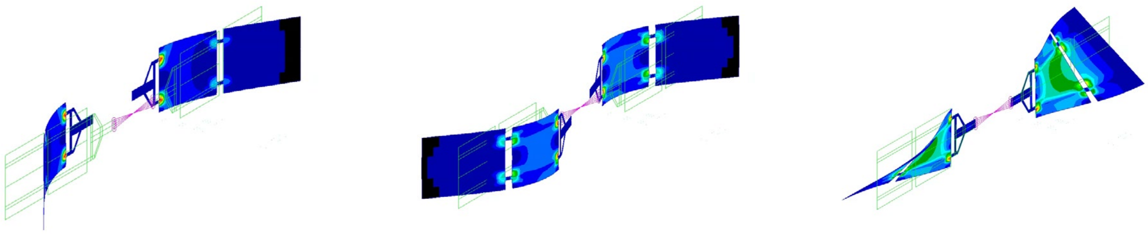
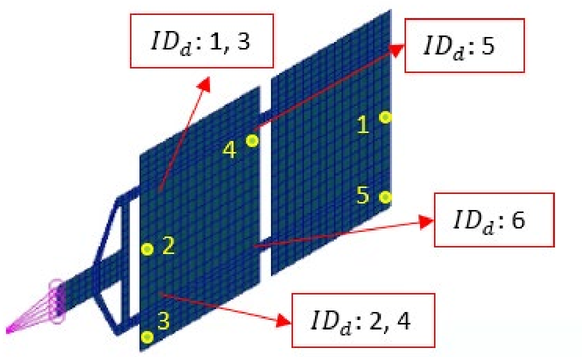


Fig. 2: Modal Strain Energy (MSE) map. From left to right, 1st mode, 2nd mode, 3rd mode



ID_d	*Description*	*Damaged FE Element*
0	Undamaged	-
1	Damage 1	602
2	Damage 2	437
3	Damage 3	601
4	Damage 4	436
5	Damage 5	435
6	Damage 6	600

Fig. 3: Overview of damages (indicated as ID_d) and sensors (indicated with numbers from 1 to 5).

Training and Validation

To generate the training set, a 3D simulator of in-orbit flexible spacecraft dynamics – developed in house [11-12] – is used to reproduce satellite attitude maneuvers. A finite element model is created for each damage scenario. Once the damaged structural sub-models, deriving from the original undamaged one, and the network of sensors are defined, the dataset generation for the training of the DNN can be set up. In detail, the followed steps are:

- The finite element structural models are imported in Matlab to perform the non-linear simulation of attitude maneuvers for the flexible spacecraft.
- Several one-, two- and three-axis attitude maneuvers are simulated by varying not only the target orientations, but also the gains of the quaternion-based PD control law to further diversify the dataset.
- Time histories from installed accelerometers sensors are recorded and saved to create the training and testing data, not before being pre-processed and normalized according to their mean and standard deviation.

Results

Several parameters are considered and optimized to improve the performance of the network: the DNN hyperparameters, the data pre-processing and the number and location of sensors. Finally, Table 1 shows the results in terms of accuracy (mean value and standard deviation) of the adopted classification network. In detail, four damages in the area of the structure associated with both highest MSE (red areas in Fig. 2) and lower MSE (green areas in Fig. 2) are considered. Despite inducing a reduced change in the system frequencies and modal shape (about 1% relative difference), the DNN shows a good classification accuracy even in this challenging case. The confusion matrix is illustrated in Fig. 4.

Table 1: Classification accuracy

Case	*Description*	*Rationale*	*Accuracy*
1	ID_d: 0, 1, 2, 5, 6 Sensors: 1, 2, 3, 4, 5	Identify the location of different damages in different MSE concentration areas (highest and second highest)	85.09% ± 4.87%

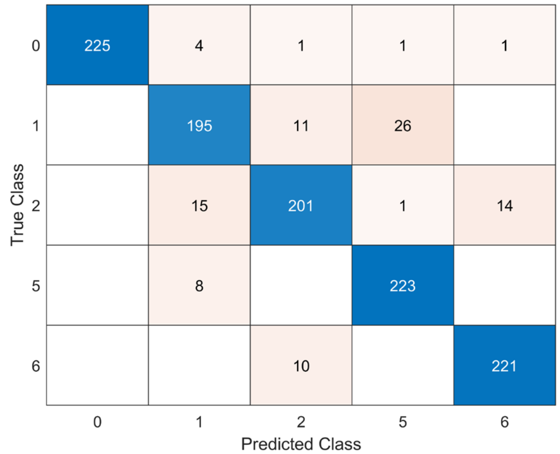


Fig. 4: Confusion matrix

Conclusions

This work has showcased the potential of LSTM networks in identifying damages in large space structures by analyzing time responses measured by sensors. The presented results are not only preparatory to carry out a laboratory experimental validation phase on a flexible spacecraft test-rig, but also propaedeutic to apply the system to several innovative composite materials. Indeed, future research endeavors could explore the possibility of training deep neural networks using real-world measured data, enabling them to operate in practical conditions and accurately predict actual damages.

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