Machine learning algorithms for Structural Health Monitoring

Optimal features selection and supervised dimension reduction

Marc REBILLAT (ENSAM, Paris), Nazih MECHBAL (ENSAM, Paris), Stéphane CANU (INSA, Rouen)

***Duration:** 6 months* ***/ Starting:** February-March 2019* ***/ location:** ENSAM Paris- INSA Rouen*

<u>Context: Structural health monitoring (SHM) of composite structures</u>

Monitoring in real-time and autonomously the health state of structures is of high interest for the industry, and more specifically for the aeronautic and civil engineering applications fields. Such a process is referred to as Structural Health Monitoring (SHM). To do so, these structures become “smart” in the sense that they are equipped with sensors, actuators and artificial intelligence that allows them to state regarding their own health. One can compare such smart structures with the human body which, thanks to its various senses and nerves, can know if it has been hurt and where. The SHM process is classically decomposed into 4 steps: damage detection, damage localization, damage classification and damage quantification.

Here the focus is put on composite structures representative of aeronautic materials. To deploy SHM to composite structures, such structures are equipped with piezoelectric elements that can be used both as sensors and actuators (see Figure 1). Each element is actuated one by one using a tone burst at high frequency (typically $\simeq 100-200$ kHz), produces an ultrasonic wave that propagates throughout the structure and that is measured by the other piezoelectric elements acting as sensors.

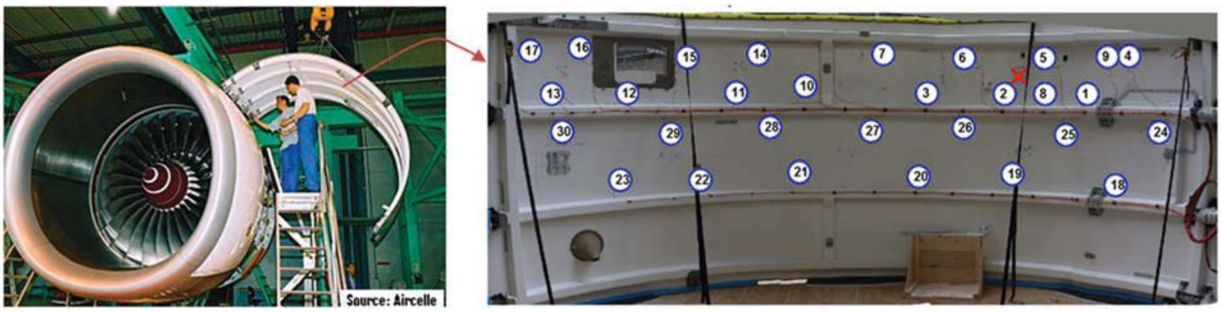

Figure 1: Example of an A380 Nacelle made of composite materials and equipped with piezoelectric elements

Mathematically speaking, if one considers a structure equipped with N piezoelectric elements and for which acquisition is performed over K samples, one naturally ends up with a matrix $\boldsymbol{M} \in \mathbb{R}^{N\times N\times K}$ at the end of the SHM process. To monitor the possible apparition of damage, measurements are first performed in a reference (or healthy) state to get a reference matrix $\boldsymbol{R}$**.** Then, during the life cycle of the structure measurements at unknown states are performed and provides the matrix $\boldsymbol{U}$**.** A number F(for ex. 20) of features (specifically called “damage indexes” in the present context) is then extracted from the matrix $\boldsymbol{\Delta}$ that corresponds to the difference between $\boldsymbol{R}$ and $\boldsymbol{U}$, $\boldsymbol{\Delta} = \boldsymbol{R} - \boldsymbol{U}$, to provide the matrix $\boldsymbol{F}_{\boldsymbol{\Delta}} \in \mathbb{R}^{N\times N\times F}$ with $F \ll K$. This matrix is the basis of the machine learning algorithms dedicated to the detection, localization, classification and quantification steps of SHM.

Machine learning perspective:

The extraction of damage-sensitive features from measurements is a process that is most powerful when it is followed by pattern recognition. Indeed, in a statistical pattern recognition paradigm for SHM, it is usually rather difficult to obtain data from damaged structures because of cost and of practical constraints. However, when such data are available, a whole new range of algorithms can be used, and the problem of damage detection, localization, and quantification can be cast as one of classification. Despite several works in this direction, there are still a number of challenges (theoretical and implementation) that hinder SHM industrial deployment, for example:

- develop efficient **data reduction**, **multi modal learning** and **ranking** for SHM process;
- develop **data-driven probabilistic algorithms** for aerostructures damage monitoring (diagnosis) and remaining useful life (**RUL**) estimation (prognosis), with uncertainty quantification;
- develop a **hybrid approach, combining machine-learning based data analytics algorithms and physics based models,** for diagnostics, prognostics and health management (PHM) of dissimilar aircraft systems;
- develop an efficient maintenance packaging for **real-time adaptive fleet maintenance management** based on continuous structures and systems health assessment;

In this work, statistical pattern recognition paradigm for SHM is considered, and we the goal is to provide a metric (how likely are SHM system outputs) helping the condition-based maintenance decisions for in-service structures. Formally, we seek for an algorithm able to solve a multi-class data classification problem in a manner that produces confidence probabilities associated with each class. This algorithm should also ideally take into account some *a priori* knowledge (physical related to the structure (geometry, material, waves properties, …) in order to speed up and increase the reliability of the diagnostic.

The multiclass SVM component, kernel selection and variable selection could be explored, as for example the multiple cores (MKL) and PLS discrimination or SVMs with integrated variable selection as in adaptive scaling. (Deep Learning, LSTM network …). A compléter

The PIMM laboratory (ENSAM, Paris) has several facilities related to SHM (numerical and experimental platforms) that could be used during the internship. Actual structures as A380 nacelles part equipped with PZT elements will be used for training and tests.

The work will take place between the PIMM laboratory (ENSAM Paris) and the LITIS laboratory (INSA Rouen).

References

C. Boller, F. K. Chang et Y. Fujino, Encyclopedia of Structural Health Monitoring, Wiley, 2009.

J. M. Nichols et M. D. Todd, «Encyclopedia of Structural Health Monitoring,» John Wiley & Sons, Ltd, 2009.

W. Staszewski, C. Boller et G. R. Tomlinson, Health Monitoring of Aerospace Structures: Smart Sensor Technologies and Signal Processing, First éd., Wiley, 2004.