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SHM implementation on a RPV airplane model based on machine learning for impact detection

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Abstract. In this work an on-working Structural Health Monitoring system for impact detection on RC airplane is proposed. The method is based on the propagation of Lamb waves in a metallic structure on which PZT sensors are bonded for receiving the corresponding signals. After the detection, Machine Learning algorithms (polynomial regression and neural networks) are applied to the data obtained by the processing of the acquired ultrasounds in order to characterize the impacts. Furthermore, this work presents the development of a mini-equipment for acquisition and data processing based on a Raspberry Pi micro-computer.

Introduction

The localisation of impacts on aerospace structures is one of the main goals of Structural Health Monitoring (SHM) systems [1]. Even a small impact at low speed can cause a crack that can become serious damage in the long run. Therefore, SHM has reached a certain level of maturity for what concerns the choice of the best sensor network for the impact detection [2],[3]. Furthermore, other works focus on the application of machine learning (ML) algorithms for the elaboration of acquired data and the prediction of the impact localisation and of the damage [4]-[8]. In the present work a ML model is built in order to characterize the real impacts on a fixed specimen in laboratory and then it is tested in the presence of vibrations due to the engine of a balsa wood RC model of the Piper J3 CUB airplane.

Experimental Setup

In a first activity, low speed impacts were performed on a 25×25 cm specimen made of aluminium alloy with density 2700 kg/m3, elastic modulus E = 72 GPa, Poisson's ratio v = 0.33 and thickness = 1.2 mm. Four piezoelectric ceramic PZT $\mathrm{Pb}[Z_{r_x}\mathrm{T}_{\mathrm{i}_{1-\mathrm{x}}}]\mathrm{O}_3$ sensors [9] (diameter equal to 10 mm) were bonded on the surface, at the four vertices of a 12.5×12.5 cm square area. The impacts were performed inside the area above by dropping a steel ball from the top of a "drop tower" built up in the AeroSpace Structural Engineering Lab (AS.S.E. Lab – University of Salento) [10]. The waves generated by the impacts were processed by a Picoscope 6402D oscilloscope connected to an Intel CPU workstation running Picoscope6 software. The processed data became the input for a ML model implemented in MATLAB, as described below. In a second activity, the vibration due to the engine were detected by the sensors bonded on the fuselage and the wings of a balsa wood RC model of the Piper J3 CUB airplane (Fig. 1). The vibrations were processed by a Pimoroni HAT Explorer Pro connected to an ARM CPU Raspberry Pi minicomputer running Python software. The processed data became the input for a ML model implemented in C++ through MATLAB Coder, run on the same Raspberry Pi.

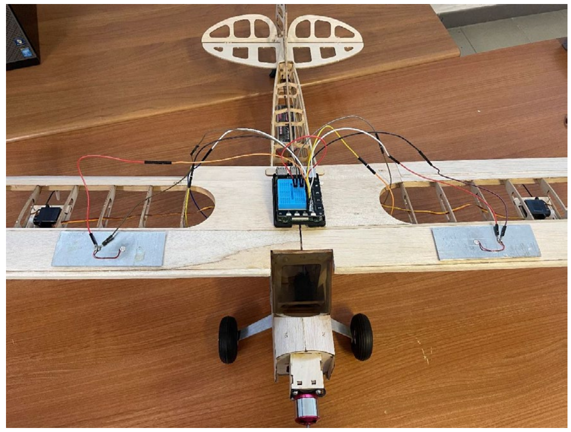

Fig. 1. Experimental setup: acquisition of the vibrations via Raspberry Pi

Machine Learning Application

In the first activity, L impacts were performed and, for each impact, four ToFs (Time of Flight) were calculated on the basis of the Lamb waves detected by the four PZT sensors. The ToF was defined as the arrival time of A0 mode of the Lamb wave to a sensor, in the range 0-40 kHz, where the A0 mode is dominant, while the S0 can be considered neglectable [11-12]. The ToF was calculated by evaluating the Short Time Fourier Transform (STFT) of the signals in the range 0-40 kHz. Because of the absence of an absolute clock signal, the differences t_1, t_2, t_3 between the ToFs at three sensors and the ToF at one reference sensor were chosen as the features for the ML application. After the evaluation of the ToFs, a dataset was built, made of L rows corresponding to the samples (impacts points) and five columns containing, for each sample, the actual coordinates (x,y) and the three ToF differences t_1, t_2, t_3. Two supervised ML algorithms, polynomial regression (PR) and artificial neural network (ANN), were applied to this dataset, in order to build models able to predict the position of an unknown impact, and to identify the best one. Considering a PR algorithm, the coordinates (x,y) of the impact are polynomial functions of the three ToF differences t_1, t_2, t_3. The building of the model consists of identifying the degree d and the coefficients θ in order to best fit a set of given data:

$$x = \theta_{x_0} + \sum_{i=1}^{3} \theta_{x_i} t_i + \sum_{j=1}^{3} \sum_{k=1}^{3} \theta_{x_{jk}} t_j t_k + \cdots \tag{1}$$

$$y = \theta_{y_0} + \sum_{i=1}^{3} \theta_{y_i} t_i + \sum_{j=1}^{3} \sum_{k=1}^{3} \theta_{y_{jk}} t_j t_k + \cdots \tag{2}$$

Fixing the polynomial degree d and extending the above equations to L impacts, it is possible to use the matrix form:

$$\boldsymbol{U} = \boldsymbol{TB} \tag{3}$$

where: $\boldsymbol{U}$ is $L\times 2$ matrix, in which the columns contain the coordinates for the L impacts respectively; $\boldsymbol{T}$ is $L\times p$ matrix, in which the p columns contain the so-called polynomial features (ToF differences, their power and relative cross multiplication); $\boldsymbol{B}$ is $p\times 2$ Design Matrix of weight coefficients θ. A subset of M impacts was used as training data, in order to calculate the design matrix $\boldsymbol{B}$ as specified in [13]. The model was validated by estimating the Mean Radial Error (*MRE*) over the M training data, the N test and total L data, where the Radial Error (*RE*) was defined as the Euclidean distance between the actual coordinates (x_i,y_i) and the coordinates $(\bar{x}_i,\bar{y}_i)$ calculated by the algorithm for the i^{th} impact. Considering an ANN, the coordinates (x,y) of the impact are calculated in the basis of the three ToF differences t_1, t_2, t_3 by computations in succession through connected nodes called neurons. Each neuron performs the computation of an intermediate output

z using the input vector t, the vector of weights w and the vector of biases b and the computation of the output a as an activation function g (a linear function in a regression problem, like a *sigmoid* one) of z:

$$z = w^T t + b \tag{4}$$

$$a = g(z) \tag{5}$$

The neurons are aggregated into layers and a shallow neural network (SNN) was chosen, consisting of only one hidden layer. As for PR, a subset of M impacts was used for the training phase of the network, that consists of an iterative procedure in order to set the weights w and the biases b of each neuron. For this procedure, three learning algorithms were compared: Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient [14]-[16]. As for PR, the model was validated by estimating the Mean Radial Error (*MRE*).

Analysis and Results

About the PR, in order to generalise the model, the calculation of ***B*** and the corresponding *MRE* was performed by the mean in a *K-Fold* cross validation procedure, considering the polynomial degrees from 1 to 7 and, for each degree, 5 different combinations of training/test sets with an 80/20 ratio. In this calculation, L (total number of impacts) was equal to 167, M (number of training impacts) was equal to 134, N (number of test impacts) was equal to 33. The best model, in terms of generalising, was chosen considering both minimum total *MRE* and minimum gap between training and test *MRE*s: this condition occurred with degree equal to 3. Moreover, the threshold 110 appeared to be the best training size: for bigger values of size there was no littler *MRE*. After the evaluation of the best degree and training size, 50 test cases were implemented, with a main result in terms of *MRE* on the entire dataset equal to **1.50** mm. About the SNN, the performances were evaluated considering all the three learning algorithms above, increasing the complexity of the model in terms of number of neurons in the hidden layer (10, 20, 30, 40, 50). The increasing in neurons number did not lead to a significant improvement of *MRE*, while the best training algorithm was the Bayesian Regularization. After the evaluation of the best neurons number and training algorithm, 50 test cases were implemented in MATLAB [17], with a training/test ratio equal to 70/30 (L = 167, M = 117, N = 50) and a main result in terms of *MRE* on the entire dataset equal to **1.20** mm. In a second activity, the vibrations due to the engine of a balsa wood RC model were acquired and processed by a Pimoroni HAT Explorer Pro connected to an ARM CPU Raspberry Pi minicomputer. The processed waveforms were used to reproduce the same vibrations on the 25×25 cm specimen using a LMS Test Lab shaker. The best ML model (based on SNN algorithm) trained and built during the first activity was then tested in presence of vibrations, obtaining a similar *MRE*. The ML model was implemented in C++ through MATLAB Coder, run on the same Raspberry Pi.

Conclusions

This work focused on the implementation of a SHM system on a balsa wood RC model of the Piper J3 CUB airplane. A machine learning model able to predict the location of low-speed impacts on aluminium plate was built and it was tested in the presence of the vibrations due to the engine of the airplane model. The best algorithm was found to be a shallow neural network trained with Bayesian Regularization procedure. The best *MRE* value was equal to 1.20 mm, configuring the model with a 70% training sample ratio and 10 hidden neurons, and a similar *MRE* was calculated in the presence of the vibrations. The results can be considered excellent, because the mean radial error falls in an acceptable range if compared to the size of the plates. Furthermore, this work presents the development of two innovative mini-equipment: (i) impact detection and wave acquisition system via Pimoroni HAT Explorer Pro; (ii) data processing and prediction via ML learning software running on a Raspberry Pi micro-computer. These two mini-systems can be considered very efficient because of their performance in terms of precision and for their little size, that allows to install it on unmanned aerial vehicles.

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