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DAMAGE SIZE QUANTIFICATION IN AERONAUTIC COMPOSITE STRUCTURES BASED ON IMAGING RESULTS POST-PROCESSING

William BRIAND*, Marc REBILLAT*, Mikhail GUSKOV* AND Nazih MECHBAL*

*PIMM Laboratory
ENSAM-CNAM-CNRS-HESAM
75013 Paris, France

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Abstract. Thanks to their high strength to mass ratio, composite materials are now widespread in the aerospace industry. Nevertheless, this type of material is subject to various internal damages and it is mandatory to monitor in real time their structural integrity. Structural Health Monitoring (SHM) is a process based on embedded sensors whose aim is to detect, locate, classify and quantify potential damages appearing in a structure in order to avoid structures catastrophic failures and to estimate their residual life. The most widely used technique to perform SHM of aeronautical structures made up of composite materials is based on the use of ultrasonic Lamb waves. However, even if robust and precise SHM algorithms exist for damage detection and localization, there is still a huge need for reliable algorithms for damage quantification. In this paper, a damage quantification strategy based on a post-processing step of the results of damage imaging method is presented. Such a method allows for damage size assessment of a delaminated area by post-processing the images produced by damage localization algorithms. Localization methods take raw signals from sensor as input and return a map of index representing the likelihood of presence of a damage over the surface of the structure under study. From this spatial probability map, region of high localization index can be identified around the estimated damage location and the area this region can be computed. A data-driven model representing the mathematical relationship between the computed area and the actual size of the damage is then inferred. The proposed method is successfully validated on numerical simulation data carried out on CFRP plate samples equipped with a stiffener and of a piezoelectric sensor-actuator network with several configurations of damage size.

1 INTRODUCTION

Maintenance is a great cost for airlines since structure checks require to ground an aircraft for several days [1]. These inspections are fixed-interval with a rate provided by the constructor. Nevertheless, as the current state of the structure is unknown, this rate is not condition-based. That is why real time monitoring of structures is of high interest in the industry and in particular in aeronautics. This research field is known as Structural Health Monitoring or SHM.

Various techniques are used to monitor possible damage apparition in a structure. The most used is the emission and reception of ultrasonic Lamb waves [2, 3]. Such waves are easy to generate at high frequencies using ultrasonic transducers (such as piezoelectric elements called PZT) making them able to interact even with small damages [4]. Moreover, Lamb waves can propagate in large structures with

low dissipation thanks to their small attenuation ratio. Structures are usually equipped with a network of PZT components acting both as actuators and sensors [5]. A classical SHM process can be decomposed in four distinctive steps [6]:

- **Detection:** evaluation of presence of a damage in the structure under study;
- **Localization:** estimation of the position of damage;
- **Classification:** identification of the damage type (crack, delamination, etc.);
- **Quantification:** assessment of the damage's size.

However, even if robust and precise SHM algorithms exist for damage detection and localization, there is still a huge need for reliable algorithms for damage quantification. Several methods dedicated to this issue have already been proposed in the literature. One method consists in computing a relevant damage index that varies with the size of the damage [7]. Another approach is to train an Artificial Neural Network (ANN) on simulated data. The size of a damage is then estimated using experimental data as an input of this ANN [8]. Statistical methods have also been investigated. Bayesian updating techniques have been applied to crack size assessment [9] and delamination [10]. Multi-class classification for damage quantification with a support vector machine have been successfully validated on a beam [11]. These methods are interesting but do not take into account spatial information available at the end of the localization step of the SHM process that may be relevant also for quantification purposes.

Localization methods are on the basis of the damage quantification approach proposed here. These methods have been extensively studied in the literature. Time-of-arrival (TOA) [12] method is a triangulation algorithm used for localization. The idea is to compute the time of flight of the wave between the actuator and the sensor and to compare this time to the one taken by the wave scattered by the damage. It gives a locus of possible positions of the damage under the form of an ellipse. This process is used with at least 3 PZTs in order to get a unique damage localization estimate. Difference time-of-arrival (DTOA) [12] are based on the same principle. In this approach difference of time of arrival of the wave scattered by the damage are computed at two sensors. This gives a hyperbola of possible positions. As in the TOA algorithm, 3 PZTs or more are necessary to assess a unique position of the estimated damage location. In the delay-and-sum method (DAS) [13] for each point of the structure under interest and each actuator-sensor path, time of arrival of the Lamb wave are computed as if there was a damage at this position. Then, the residual of the signal is computed (*i.e.* the difference of magnitude between the reference signal and the one that is tested). For each tested point, the resulting damage index map is averaged over each actuator-sensor path. This method showed great results on an aluminum plate [14] and on a composite plate [15, 16]. RAPID (Reconstruction Algorithm for the Probabilistic Inspection of Damage) [17] algorithm consists in computing the probability of a defect occurrence using the relative amplitude of the signal change on each actuator-sensor path. This probability is computed using the signal difference coefficient and a ratio representing how far is the point from the direct path. The defect distribution probability within the sensor network is then expressed as a linear summation of all the signal change effects of every pair. For each point the signal is averaged between all path. This method has been successfully tested on aluminum plates [15].

Some attempts to post-process the results of the damage imaging methods mentioned above for damage size quantification purposes have already been tried in the literature. TOA algorithm has been used to quantify the size of an impact damage on a composite panel [18, 19]. This method has been validated on experimental and numerical data. Damage imaging methods results have also been applied to assess the position of crack tips. The size of the crack is then estimated from the area computed between the

tips position [20, 21]. However, none of these methods addressed the case of a delamination type damage which is crucial in composite structures.

In this paper, an alternate damage quantification strategy based on a post-processing step of the results of damage imaging method and focusing on delamination-type damage is presented. Such a method allows for damage size assessment of a delaminated area by post-processing the images produced by damage localization algorithms. Localization methods take raw signals from sensor as input and return a map of index representing the likelihood of presence of a damage over the surface of the structure under study. From this spatial probability map, region of high localization index is identified around the estimated damage location and the area of this region is computed. A data-driven model representing the mathematical relationship between the computed area and the actual size of the damage is then inferred. As more and more aeronautic structures are made of composite [22], SHM processes have to be tested on this type of material. That is why the proposed method is validated on numerical simulation data carried out on CFRP plate samples. These samples are equipped with a stiffener and of a piezoelectric sensor-actuator network with several configurations of damage size. The proposed method is detailed in Sec. 2 and validated on numerical data coming from simulation of a composite plate equipped with a stiffener described in Sec. 3. Results are shown and discussed in Sec. 4.

2 METHOD

The workflow of the damage size quantification algorithm based on the post processing of damage imaging algorithms is divided in two steps. The first one is the learning step. It consists in building a data-based model from numerical or experimental data. These data are raw signals from actuator and sensor placed on the structure under study for multiple sizes of damages. In the second step, the size of an unknown damage is predicted with the model previously built. The overview of the method is depicted in Figure 1. N_{sens} stands for the number of sensors, N_{rep} corresponds to the number of repetitions of the measure, N_{dam} represents the number of damage cases and N_{conf} stand for the number of PZTs configurations. A PZTs configuration is a subset of all the transducers glued to the structure. For example in a case where a sample is equipped with 3 PZTs, measures can be done with 4 different PZTs configurations: [1,2], [2,3], [1,3] and [1,2,3].

2.1 LEARNING STEP

For any localization algorithm, raw signals are first denoised, filtered and time-aligned for each damage case (*i.e.* for each different size of damage available in the data base used for learning). The group velocity of the ultrasonic Lamb waves is then computed to be used in the localization method picked by the user: TOA, DTOA, RAPID or DAS. Once the localization process is done, a damage localization index (DLI) map is obtained for each damage case. Next, the resulting DLI maps are post-processed for all damage cases. A threshold function is applied to the image to extract a binary map. Then an image segmentation algorithm is used to partition the binary DLI map in several regions of interest and to select the one surrounding the estimated damage position. This region is called “*high DLI region*” and its area is computed. At this point, the area of the “*high DLI region*” has been computed for multiple sizes of damage. The idea is now to learn the mathematical relationship existing between the “*high DLI region*” areas and the actual damage sizes. A regression is then performed on these data in order to infer the damage size quantification model.

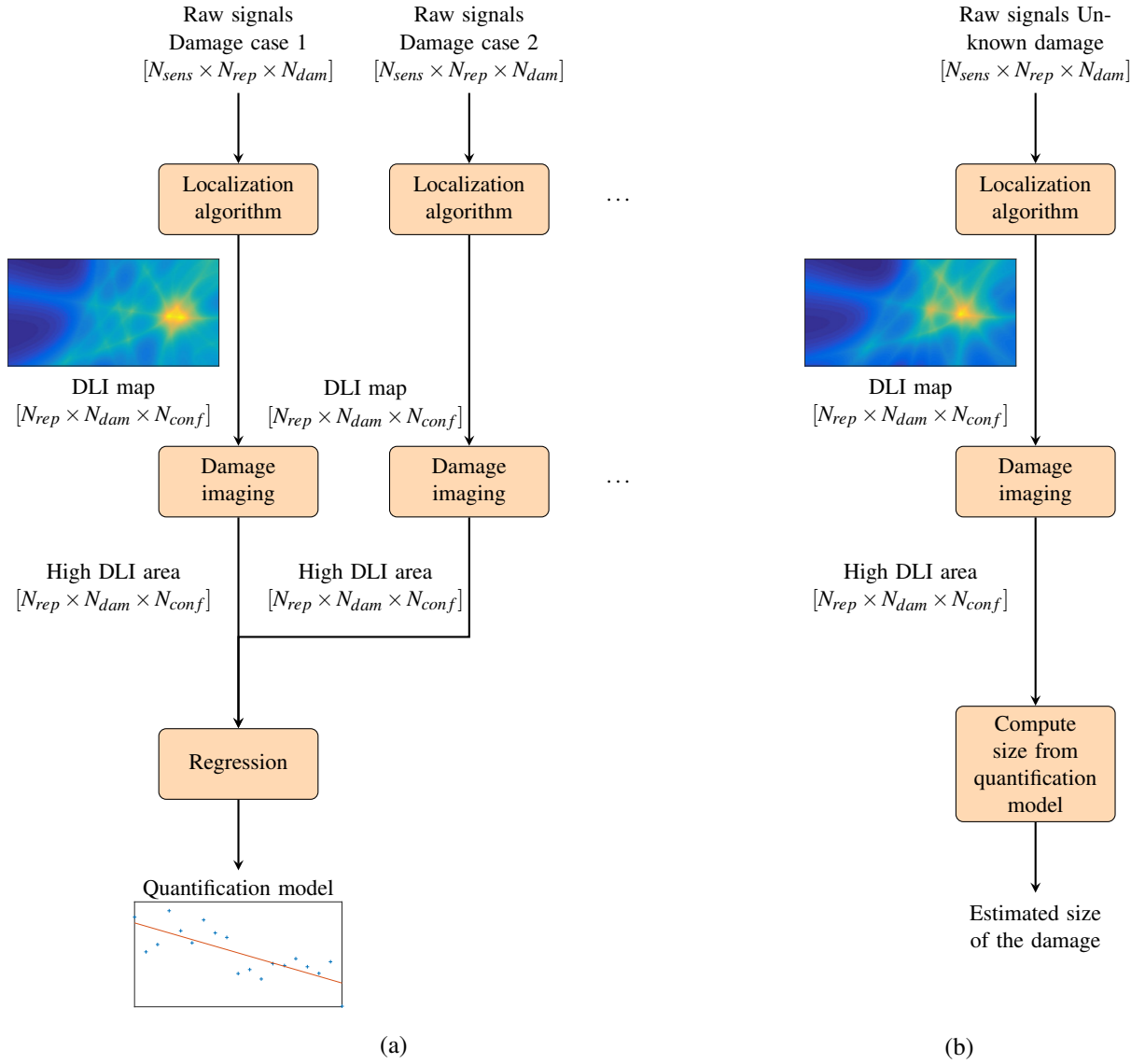


Figure 1: Overview of the damage size quantification algorithm based on the post processing of damage imaging algorithms. Description of the learning step (a) and the prediction step (b).

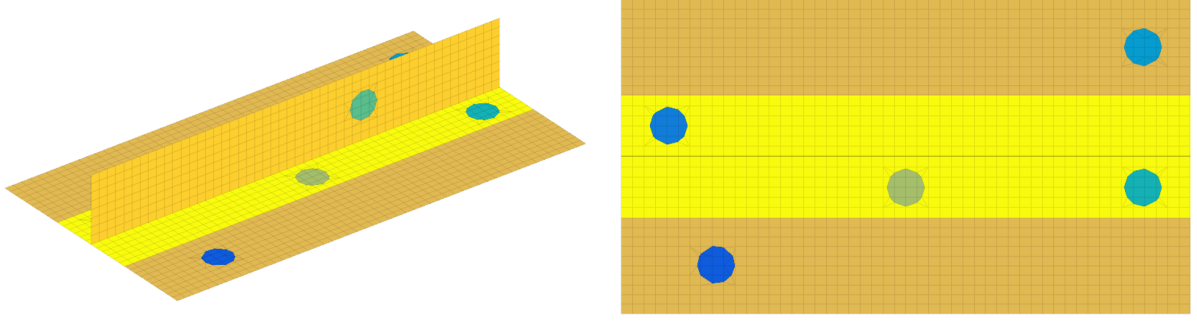


Figure 2: FEM model of the stiffened panel used for simulation

2.2 PREDICTION STEP

Now that a quantification model has been built, it can be used to estimate the size of an unknown damage. In this prediction process, raw signals coming from the structure in an unknown damaged state are denoised, filtered and time-aligned. Then the same localization algorithm and damage imaging process used for the learning step are applied. Finally the estimated size of the unknown damage is computed from the quantification model using the high DLI area computed.

3 STRUCTURE UNDER STUDY

The method described in this paper is validated using numerical data. The structure under consideration is a stiffened composite panel. The structure is made of graphite-epoxy plies with the stacking sequence $[45^\circ/0^\circ/45^\circ/90^\circ/-45^\circ/0^\circ]$ in the skin. The properties of one ply are given in Table 1.

Table 1: Material properties

	Density [g/cm^3]	$E(0^\circ)$ [GPa]	$E(90^\circ)$ [GPa]
Unidirectional	1.57	163	10
Woven	1.56	85	79

The structure is equipped with five PZTs components that can be used both as sensor and actuator. The FEM model with the PZT and damage position is shown in Figure 2. Coordinates of these piezoelectric elements and of the simulated damage can be found in Table 2.

Table 2: Coordinates of PZT elements and damage center

	PZT1	PZT2	PZT3	PZT4	PZT5	Damage
x(mm)	50	25	275	275	200	150
y(mm)	25	98.8	140	66.3	82.5	66.25

Damages have circular shape with a radius varying between 1mm and 10mm by step of 0.5mm leading to 19 damage cases. The damage is represented by a decrease of the Young modulus of 90% in the

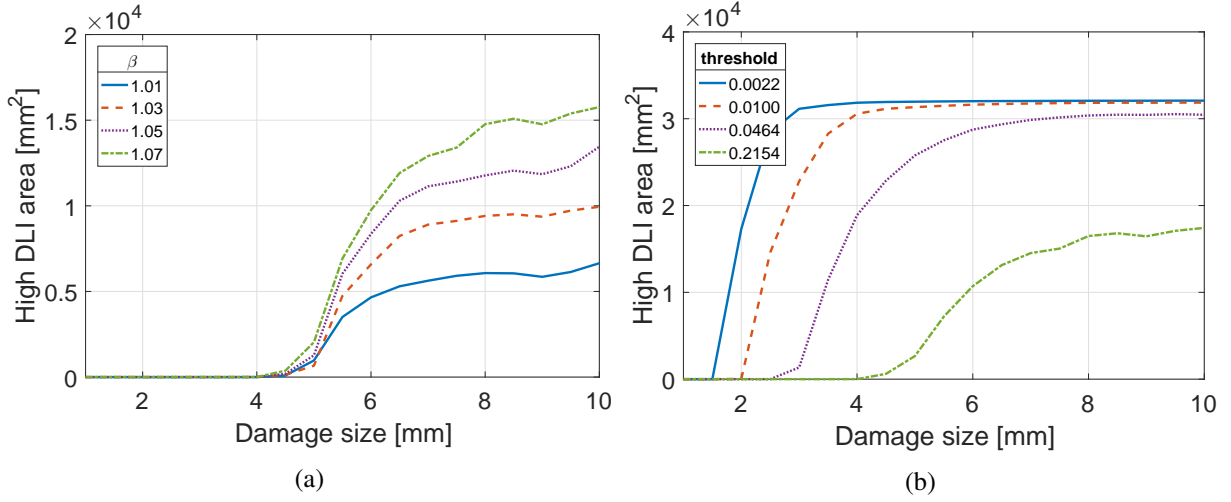


Figure 3: Sensitivity of the RAPID method to β parameter (a) and threshold (b).

damaged area. A healthy case *i.e.* without damage is used as reference for comparing the signals. Simulation have been conducted using the *Matlab* toolbox SDTools [23]. Signal used is a 5-cycles tone burst of 160 kHz central frequency with random noise in order to introduce variability in the data. The signal to noise ratio, as defined in Eq. (1), is 70dB.

$$SNR = 10 \log_{10} \left(\frac{P_{signal}}{P_{noise}} \right) \quad (1)$$

where P_{signal} and P_{noise} are signal and noise power respectively. For each damage case 10 repetitions have been performed. The sampling frequency is 2 MHz. Localization algorithm can be performed in two running mode. The first one is called “*test*”. It means that only the first repetition of the healthy state and the first repetition of the damage case will be compared. In the other mode called “*full*” each repetition is compared of the healthy state is compared with each repetition of the damage case in order to take the take the variability of the measure into account.

4 RESULTS AND DISCUSSION

4.1 PARAMETERS

The damage quantification method proposed in this paper has been tested with several localization algorithms: TOA, DTOA, RAPID and DAS. Each of these algorithms depend on a parameter. In the TOA and DTOA algorithms, a decay rate of an exponential windowed function applied is introduced to reduce secondary reflections [12]. DAS depends on the number of samples over which time integration is performed [13]. In the RAPID approach the user can set a parameter called β corresponding to the the spread of the ellipses around each path [15]. Moreover, the damage quantification method itself also has one parameter which is the threshold level. To show the influence of the parameters tuning, sensitivity of the RAPID algorithm to β parameter and threshold is depicted Figure 3.

Thus, for each localization method the best set of parameters has to be found in order to get the damage size regression with the minimum error. Computations were performed for a range of parameters in order to find the best set of parameters in this range. These computations were run in “*test*” mode. Table 3 provides the best sets of parameters that have been found. The regression performed here is a

cubic regression. One can notice that the best threshold value hardly varies between each method. For TOA and DTOA the ellipse or hyperbola shape of the high DLI region implies changeability of the high DLI area computed, leading to irregular variation of the goodness of fit over the decay parameter. Thus, finding a value of this parameter that minimize the error of the regression for any threshold value cannot be achieved efficiently. On the opposite, DAS method shows no influence of its specific parameter in the regression. RAPID algorithm gave better regression results with a β parameter slightly greater than 1 as noticed in [15].

Table 3: Parameters and best set of parameters for each localization method

	Localization parameter	Best localization parameter	Best threshold value
TOA	Decay rate of an exponential windowed function applied to reduce secondary reflections.	$6.0 \cdot 10^{-6}$	0.22
DTOA	Decay rate of an exponential windowed function applied to reduce secondary reflections.	$7.0 \cdot 10^{-6}$	0.22
DAS	Number of samples over which time integration is performed.	11	0.46
RAPID	Parameter set to adjust the spread of the ellipses around each path.	1.125	0.22

Once these best parameters have been selected, results are shown in Fig. 5. It appears that DAS and RAPID show a clear correlation between high DLI area computed and the actual size of the damage. However, results obtained with TOA and DTOA demonstrated poor regression quality.

Once these parameters have been found, the method was run in *full* mode. The quantification model was inferred using the first 14 damage cases *i.e.* from 1mm to 7.5mm. Next, the size of the damage for greater sizes are estimated as depicted in the Figure 1a. In an industrial context it corresponds to building a model from small size of a damage and use this model to estimate future size of the damage.

The estimated sizes are compared with the actual size of the damages in the Table 4 and the Figure 5. It appears that quantification model built with DAS or RAPID methods give accurate results whereas model inferred with TOA or DTOA show poor precision when the size of the testing damage move away from the learning range. It could be explained by the difference between these two types of method. In one hand, TOA and DTOA only deal with time of arrival of the signals which is not influenced by the size of the damage. On the other hand, DAS and RAPID take amplitude of the signals into account which make the results more influenced by the size of the damage. Another reason of this difference could be the shape of the high DLI region which has great influence on the quality of the regression. In the TOA and DTOA, high DLI region is made up of ellipse or hyperbola which area does not clearly vary with the damage size. On the contrary high DLI region in the DAS and RAPID methods is circular and the high DLI variation is monotonic over the size of the damage which lead to a more accurate model. Another point is that in DAS and RAPID method high DLI computed is equal to zero for damage size under 4mm. It means that can only be build with damage greater than this value. Nevertheless this limitation is not an issue since in aeronautical applications only damages of 20mm of radius or more are sought. Finally, DAS method results is constant for each predicted damage size.

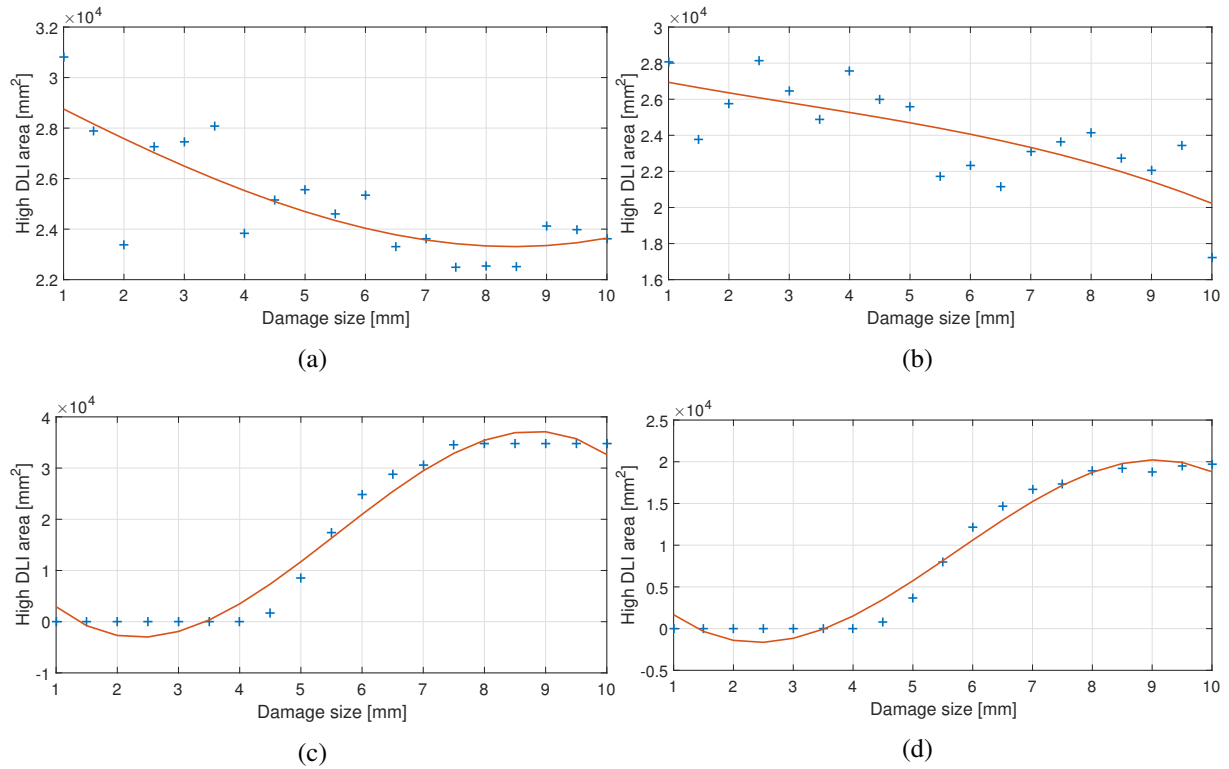


Figure 4: Results with best set of parameters for TOA (a), DTOA (b), DAS (c) and RAPID (d) methods. The line is the regression relation between high DLI area and damage size.

5 CONCLUSION

In this paper, a damage quantification strategy based on a post-processing step of the results of damage imaging method has been presented. Such a method allows for damage size assessment of a delaminated area by post-processing the images produced by damage localization algorithms such as TOA, DTOA, DAS and RAPID. From these images, region of high localization index can be identified around the estimated damage location and the area of this region can be computed. A data-driven model representing the mathematical relationship between the computed area and the actual size of the damage is then inferred. The proposed method has been successfully validated on numerical simulation data carried out on CFRP plate samples equipped with a stiffener and of a piezoelectric sensor-actuator network with several configurations of damage size. Results using RAPID method showed particularly promising results.

Future work will be focus on the validation of this method using experimental data.

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Table 4: Error between the size estimated with the quantification model and the actual size of the damage in *full* mode.

Localization method	Actual damage size [mm]	Predicted damage size [mm]	Mean relative error (in%)	Standard deviation error (in %)
TOA	8.00	7.44	7	$4.15 \cdot 10^{-2}$
	9.00	6.83	24	$6.19 \cdot 10^{-2}$
	10.00	7.01	30	$4.83 \cdot 10^{-2}$
DTOA	8.00	6.92	13	$7.03 \cdot 10^{-2}$
	9.00	3.69	59	$5.40 \cdot 10^{-1}$
	10.00	11.83	18	$1.90 \cdot 10^{-2}$
DAS	8.00	7.37	8	$9.76 \cdot 10^{-15}$
	9.00	7.37	18	$2.79 \cdot 10^{-15}$
	10.00	7.37	26	$4.46 \cdot 10^{-15}$
RAPID	8.00	7.47	7	$1.52 \cdot 10^{-3}$
	9.00	7.45	17	$1.67 \cdot 10^{-3}$
	10.00	7.60	24	$3.25 \cdot 10^{-3}$

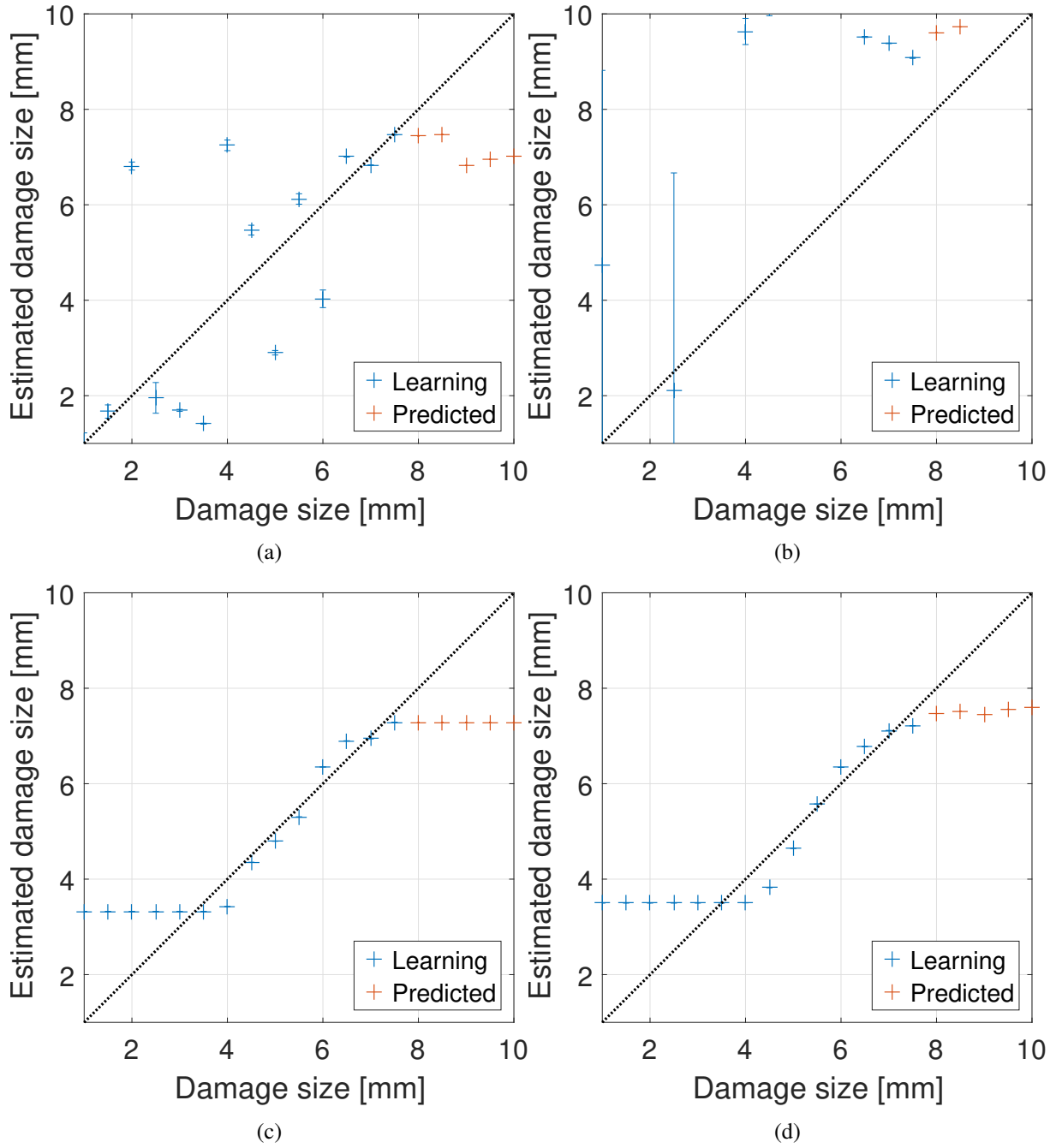


Figure 5: Estimated damage size computed with the data-driven model built versus the actual size of the damage. The dotted line corresponds to an exact prediction. Localization algorithms used in the method are TOA (a), DTOA (b), DAS (c) and RAPID (d).

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