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Temperature Compensation for Damage Detection in Composite Structures using Guided Waves

Maria Moix Bonet[1], Benjamin Eckstein[2], Peter Wierach[1]
1 Germany Aerospace Center, Germany, Maria.Moix-Bonet@dlr.de
2 Airbus Operations GmbH, Germany, Benjamin.Eckstein@airbus.com

Abstract

Guided wave based SHM poses a suitable technique in terms of damage detectability in composite structures with complex geometries. One of the main challenges for the application of the technique resides in the broad spectrum of environmental and operational conditions of an aircraft. A test series including changing temperature and realistic impact damages has been performed to evaluate data normalization approaches. Within the EU-funded DEMETER project, composite plates with co-bonded structural elements and an integrated SHM network have been manufactured for testing. The presented work focuses on the damage detection in varying temperature conditions using a data-driven method. The data-based approach addresses the damage identification as a pattern recognition problem, generating knowledge from previously collected data. The key aspects of this article include the extraction of the damage relevant features, the pattern recognition concept for the data normalization and the subsequent damage detection.

1. Introduction

The introduction of composite materials in aeronautics has brought numerous advantages although it requires exhaustive inspections in particular scenarios, such as accidental damages. As a result, Structural Health Monitoring (SHM) has gained interest as a cost and time effective alternative to non-destructive inspection (NDI).

Guided wave based SHM poses a suitable technique in terms of damage detectability in composite structures with complex geometries. One of the main challenges for the application of the technique resides in the broad spectrum of environmental and operational conditions of an aircraft. Many damage identification techniques by means of guided waves use a data-driven approach based on a reference data set and changes in the environmental and operational conditions represent a source of variability in this acquired data set. Therefore, damage identification can only take place after the differentiation between the signal changes caused by damage from the ones caused by operational and environmental variation. This process of differentiation is coined in SHM as data normalization.

A test series including changing temperature and artificial as well as realistic impact damages has been performed to evaluate data normalization approaches. The temperature conditions have been derived from a representative operational framework for commercial aircraft. Within the EU-funded DEMETER project, composite plates with co-bonded structural elements and an integrated SHM network have been manufactured for testing.

The presented work focuses on the damage detection in varying temperature conditions using a data-driven method. The data-based approach addresses the damage identification as a pattern recognition problem, generating knowledge from previously collected data. The key aspects of this article include the extraction of the damage relevant features, the statistical model for the reference data set and the subsequent damage detection. In preparing a manuscript, authors are solely responsible for the quality and appearance of the final product.

2. Specimen manufacturing and environmental tests

Four CFRP specimens with dimensions 500x500 mm^2 have been manufactured to conduct the temperature tests. The specimens are manufactured in two different configurations to test the effect of structural features on the wave propagation. Half of the specimens are simple flat plates and the other half contains an additional omega stringer. Figure 1 illustrates a specimen with stringer before the autoclave process. The added feature provides more complex guided ultrasonic wave propagation, including mode conversion and reflection at the stringer.

Piezoelectric transducers are co-bonded to the plate during the curing process in the autoclave. A total of 8 transducers are integrated on each specimen in a regular distribution, as depicted in Figure 1 for a simple plate. These piezocomposite DuraAct™ transducers from PI Ceramic are individually encapsulated in an epoxy matrix to ensure durability and electrical insulation.

The environmental tests have been performed in a climate chamber (Vötsch VCS3 4034-5) under temperatures between -40°C and 85°C. The automated acquisition of data occurred by means of a National Instruments measurement Platform operated through a Labview based User Interface.

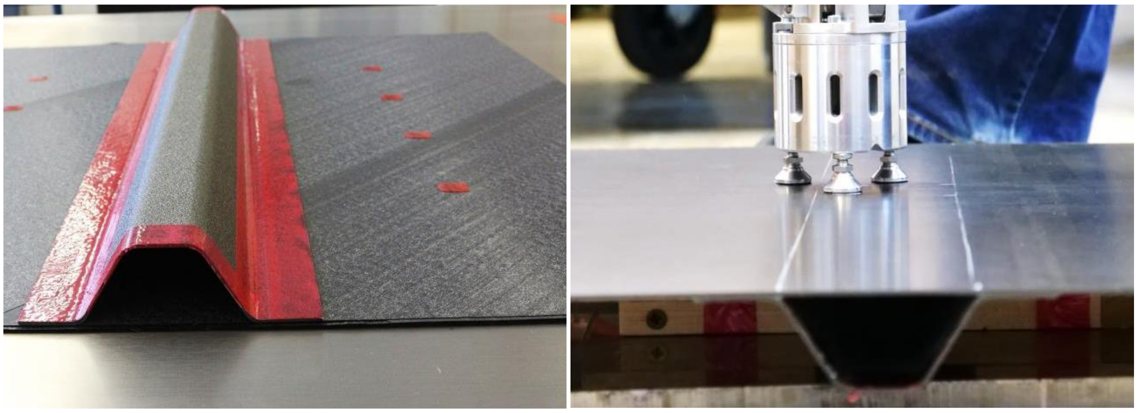

Figure 1. Specimen with stiffener and transducers prepared for Autoclave (left) and impact with gas gun (right)

3. Damage detection in temperature changing conditions

The damage detection method contains three main steps: the signal decomposition with Matching Pursuit (MP), the generation of a probabilistic model following the Gaussian Mixture approach and the evaluation of the damage indicator based on the Mahalanobis Squared Distance (MSD).

3.1 Feature extraction with Matching Pursuit

MP was developed in 1993 by [1] and decomposes the signal into elements included in an over complete dictionary of functions. The MP follows an iterative process where the program keeps the most contributive element of the dictionary per iteration until the residual signal is below a threshold. This process identifies and separates the wave packets present in the signal to then reconstruct it as a weighted sum of elements from a dictionary.

Matching pursuit is a greedy algorithm that selects the dictionary function that captures the most energy of the signal, emphasizing global fit over local fit. To account for this fact and obtain consistent results over the large temperature range a constrained MP similar to [2] is performed, where information of available analysis in similar temperatures is taken as a starting point for the next MP decomposition. Two of the extracted features with MP, the time of flight and amplitude of the first arrival, are illustrated in figure 2.

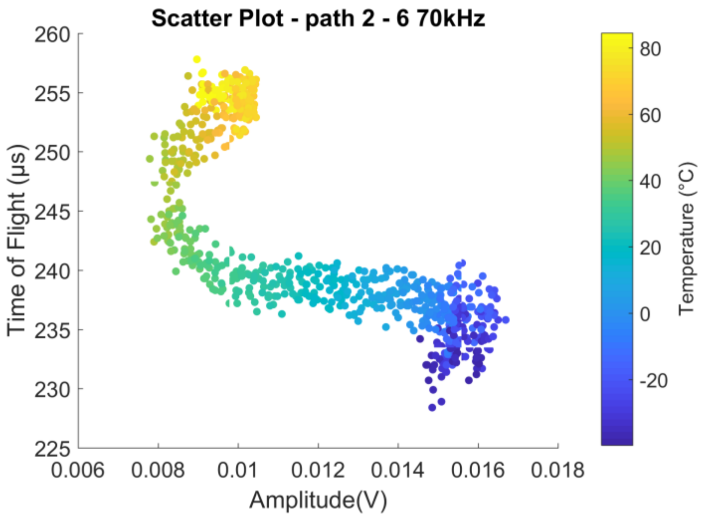

Figure 2. Extracted ToF vs Amplitude of single actuator-sensor pair over temperature range

3.2 The Gaussian Mixture Model

The Gaussian mixture models the extracted features over the temperature range with a combination of normally distributed subpopulations. The Gaussian Mixture Model (GMM) has the ability to represent a large class of sample distributions, forming approximations to arbitrarily shaped densities ([3]). This adaptation to densities with variable forms is suitable to model the feature changes over a large temperature range. GMM has been applied in vibration-based condition monitoring to detect damage in a gear box ([4]). In the field of SHM, Ren et al. propose in [5] a GMM approach for a guided wave based monitoring system applied in composite structures.

A Gaussian mixture model is a weighted sum of K Gaussian probability density functions represented by the equation,

$$p(x|\lambda) = \sum_{k=1}^{K} \omega_k f(x|\mu_k, \Sigma_k) \tag{1}$$

with ω_k being the mixture weights and $f(x|\mu_k, \Sigma_k)$ the individual Gaussian densities. The Gaussian mixture model is a function of the mean vectors, covariance matrices and mixture weights from the component densities, described with the notation,

$$\lambda = \{\, \omega_k, \mu_k, \Sigma_k\}, \qquad k \;=\; 1, \ldots, K \tag{2}$$

Each component density is a Gaussian function of the form,

$$f(x|\mu_k, \Sigma_k) = \frac{1}{(2\pi)^{D/2}|\Sigma_k|^{1/2}} exp\left\{-\frac{1}{2}(x-\mu_k)^T {\Sigma_k}^{-1}(x-\mu_k)\right\} \tag{3}$$

with mean vector μ_k covariance matrix Σ_k and D dimensions of the feature vector.

Expectation Maximization is then used to estimate the mixture model's parameters. Expectation maximization is an iterative technique for maximum likelihood estimation, which maximizes the probability of the observed data given the model parameters. A two-dimensional example of the GMM is depicted in figure 3, with a feature vector including the ToF and amplitude over the tested temperature range.

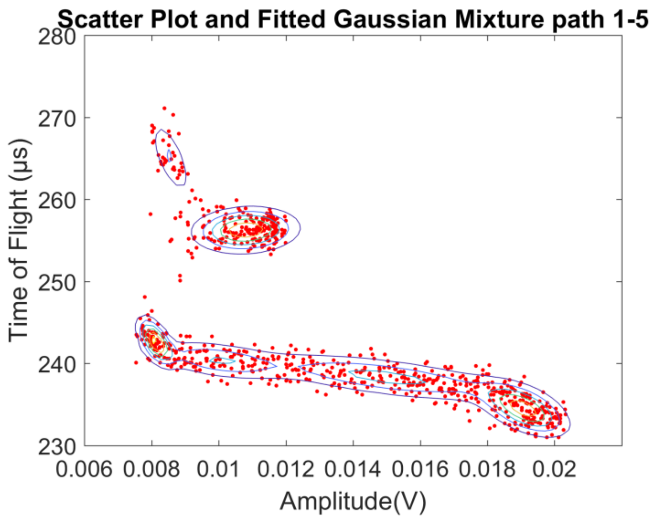

Figure 3. ToF vs Amplitude of actuator-sensor pair over temperature range with fitted GMM

3.3 Outlier detection with the Mahalanobis squared distance

The Mahalanobis squared distance defines the distance between the features extracted from the current acoustic signal and the GMM of the baseline set in the multidimensional feature space. The Mahalanobis squared distance is useful to find multivariate outliers, which indicates unusual combinations of the extracted features. This distance has been successfully applied as an outlier detector in multivariate SHM approaches such as in [6] and [7]. The measure is represented by the equation

$$D_i = (\{x_i\} - \{\bar{x}\})^T [S]^{-1} (\{x_i\} - \{\bar{x}\}) \tag{4}$$

where $\{x_i\}$ is the potential outlier, $\{\bar{x}\}$ is the mean vector of the baseline observations and [S] the baseline covariance matrix. The new feature vector $\{x_i\}$ is labeled as an outlier if it exceeds a defined threshold value. The threshold value is obtained calculating the 1 per cent of the reference data with a higher Mahalanobis squared distance from the GMM.

The method only detects an outlier due to damage if the influence of damage on the extracted features is orthogonal to the temperature influence. An example is depicted in figure 3: the amplitude decreases with damage presence while the time of flight remains unchanged. The extracted features in damaged state produce unusual combinations of values not present in the baseline data set throughout the temperature range.

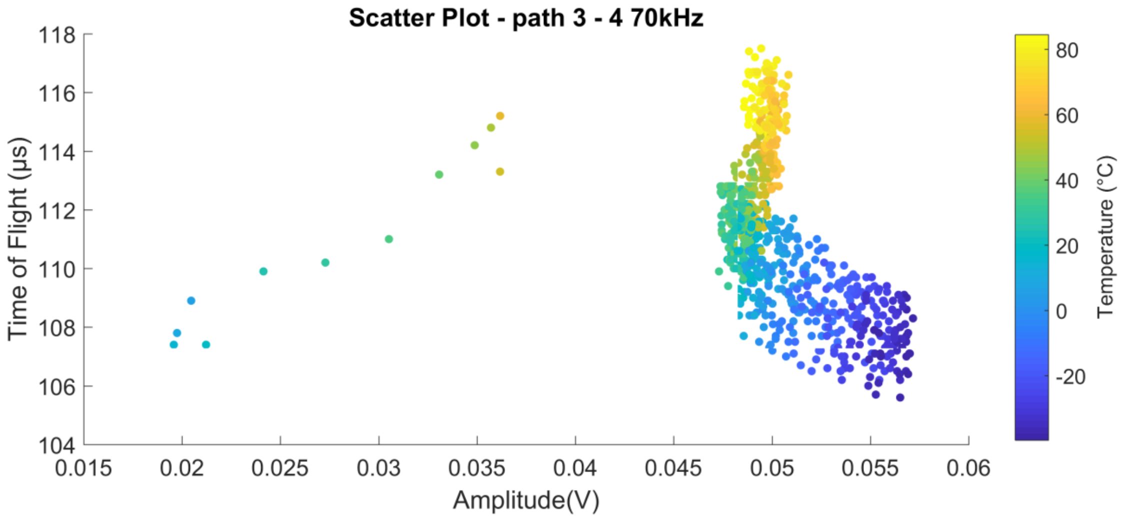

Figure 3. ToF vs Amplitude of actuator-sensor pair over temperature range: baseline vs. damaged features

3.4 Experimental evaluation

The temperature test series started with three temperatures cycles ranging from -42°C until 85°C and the periodic interrogation of the transducer network to obtain a reference data set. Afterwards several artificial damages were arbitrarily placed with again changing temperatures going from -10°C to 50°C, alternating with temperature cycles where no artificial damage was placed. The temperature test series concluded with realistic impact damages and a final temperature cycle from -42°C to 85°C.

After the data acquisition, the dynamic response of each actuator-sensor pair is sparsely represented using Matching Pursuit. The parameters of this sparse representation are used as feature vectors. In the feature space a Gaussian Mixture Model fits the extracted feature vectors of the reference data set into a weighed combination of normal distributions. After determining the threshold with the reference data set, the rest of the data is subjected to the outlier analysis based on the Mahalanobis squared distance. This process is repeated for all individual actuator-sensor pairs.

Figure 4 summarizes the damage detection during the temperature series. The plot depicts the outlier analysis for the different artificial and realistic damage states. A plot line corresponds to an actuator-sensor pair and all available temperatures are included in the analysed signals.

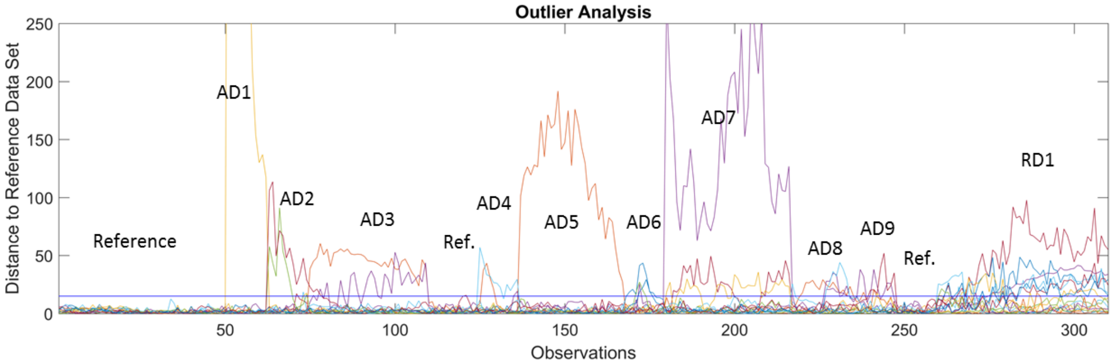

Figure 4. Outlier analysis of the temperature series with artificial (AD) and realistic (RD) damages

The outlier analysis detects damage presence on single paths, depending on the damage location. Moreover, the damage is detected consistently over the temperature range.

This works presents only the first step in the hierarchical damage identification process: damage detection ([8]). Damage localization can be performed with a reconstruction algorithm for probabilistic inspection of damage ([9]) as presented by the authors in [10], where impact damages were accurately localized in a realistic aircraft composite door surround structure.

3.5 Discussion

The advantages of the approach are the flexibility in the statistical model, the suitability for stiffened composite structures and the possibility to tailor the features extracted from the sparse reconstruction to be sensitive to certain characteristics of the dynamic response.
The limitations of the approach start with the need of a large data set over a representative temperature range to create the reference. One of the reasons of using MP for the feature extraction is the possibility to obtain these features with simulation, which would ease the effort to create a reference data set. A second limitation resides in the damage detection: the damage effect needs to be orthogonal to the temperature

effect to identify the state as an outlier. Otherwise, the temperature information should be included in the damage identification process.

4. Conclusions

A data driven damage detection approach for composite stiffened structures has been presented. The method includes a signal feature extraction based on Matching Pursuit, the statistical modelling of the reference data set with a Gaussian Mixture Model and the subsequent damage detection with an outlier analysis using the Mahalanobis squared distance.

Future work focuses on the one hand on a deeper analysis of the temperature and damage effects on the extracted features to improve the damage identification. On the other hand, this project pursues a more realistic representation of the environmental variations and will include humidity as an additional environmental factor to account for.

Acknowledgements

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