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Predicting damage location information based on single actuator-sensor-path information using regularised multilinear regression

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Abstract. In structural health monitoring with guided ultrasonic waves, probability reconstruction algorithms are a method to locate a damage. They work by calculating the probability for each actuator-sensor-path on whether there is a damage on the path or not. By superposition of each path and its damage probability, a damage localisation is done. The disadvantage of this is, that the damage localization resolution is limited by the number of paths crossing each other.

To overcome this, the hypothesis of this investigation is that the information of a path can not only be used to determine whether a damage is present, but that additional information about the location within the path can be calculated as well. This way a localization resolution can be higher than by only relying on the path density.

To verify this assumption, an experimental setup was chosen in which the path lengths always remain the same while the distance between damage and the direct path varies. This is implemented by a moving ultrasonic microphone simulating the sensor. The varying distance is the local information, which is determined in this study using the information of a single path. For this purpose, a prediction is calculated using regularised multilinear regression. The input features are characteristic values of five sections of the sensor signal in the time domain. The sections are manually chosen based on arriving wave events.

The result confirms the hypothesis. Therefore, it is plausible to increase the detection resolution of probability reconstruction algorithms by calculating damage location estimations for each path.

Keywords: structural health monitoring, ultrasonic guided wave, machine learning, probability reconstruction algorithm, damage localisation

Introduction

Multiple damage localisation methods can be found in the literature for guided wave based Structural Health Monitoring (SHM). The triangulation method, for example, locates damage accurately but is prone to failure in complex structures, due to the variety and interference of reflections [1]. The delay and sum algorithm, another localisation method, achieves satisfactory results with few sensors but in-depth knowledge of the structure, such as the waves group velocity, is crucial for an accurate damage localisation [2]. Thus, this method is

problematic in complex structures as well [3]. Probability reconstruction algorithms have been used for damage localisation based on guided waves as well. This method needs a higher density transducer network, but is applicable in complex structures, [4]. It also does not need information about the structure, which widens the operation possibilities [5]. Because of the wide application cases this study takes a closer look at probability reconstruction algorithms. The probability reconstruction algorithm uses damage indices such as the correlation coefficient ([6]) to determine whether a damage is on the path between the actuator and the sensor or not. To map this information onto a geometry the probability reconstruction algorithm uses an ellipse around the actuator and sensor, stating, that there is a probability of a damage in this area. To pinpoint the location of a damage multiple overlapping paths are necessary. [5] As single damage indices show a low sensitivity to damages, which locate offside the direct actuator-sensor-path, the damage sensitive area of one path is narrow and a high areal transducer density is needed.
With the goal to reduce the number of piezoelectric transducers per area and to improve the accuracy of the damage localisation, this work focuses on achieving an offside path damage sensitivity, while gaining additional local information from on paths signal. The goal consists in predicting the distance between the actuator-sensor-path and the damage. To obtain the location prediction, multiple features are calculated for several parts of the paths time signal and are used in a regularised multilinear regression process.

1. Experimental Setup

The goal of this survey is to investigate and develop the ability to predict the distance between the actuator-sensor-path and a damage (Fig. 1, a). Therefore, an experimental setup was used, in which multiple signal paths with varying distance to a damage are recorded: a plate with the dimensions of 500 x 500 mm is used for this purpose (carbon fibre-reinforced plastic; 2.1 mm thickness; quasi-isotropic: [0 90/ +45/ -45/ 0 90/ +45/ -45/ 0 90] with 0 90 being a woven layer and ±45° being unidirectional layers). In the middle of it a piezoelectric transducer (DuraAct) is bonded to the structure and used to generate ultrasonic waves. To record the ultrasonic waves an air coupled ultrasonic scanner is used (Hillger NDT GmbH, Fig. 1,c). This was chosen as the system is capable of recording a signal with a spatial resolution of 2 mm on both axes, therefore creating a larger database than it would be possible with bonded piezoelectric transducers as sensors. The sensor used is a DeltaTron Free-field ¼'' Microphone Type 4954A and recorded with a sampling frequency of 10 MHz for a time of 300 µs.
The observed damages are induced by a mobile impact gun (Ingenieurtechnische Dienstleistungen Gallus Lindner) in four different energy settings of 5 J, 7.5 J, 10 J and 2.5 J. The damages are located equidistant from the actuator and the plate edge, as shown in Fig. 1, b.
The signals acquired in a specific circular section (sensing points cluster) behind the damage have been chosen for this analysis. The signal path length is 170 ±3 mm. The maximum distance between a direct actuator-sensor-path and the damage location is 65 mm. This is chosen such that the effect of the neighbouring damages are less dominant than the investigated damage. With the spatial resolution of 2 mm and a chosen pathlength accuracy of ±3 mm 1114 paths are investigated. The investigated points are depicted in the blues clusters in Fig. 1, b.
For a baseline signal a pristine plate was evaluated in the same way.

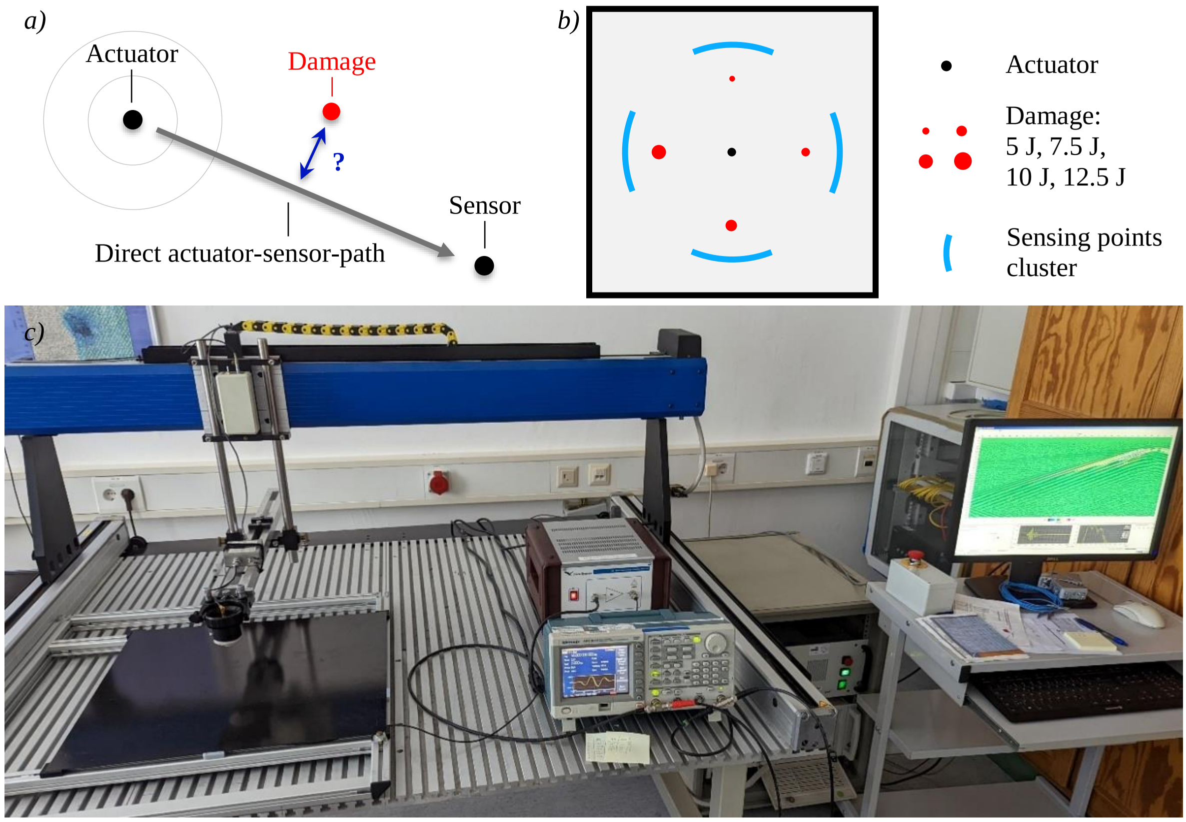

Fig. 1. a) Schematical view of the distance prediction between damage and direct actuator-sensor-path, b) schematical view of the specimen, c) experimental setup of the data acquisition

In the following the scanning points, which shall represent the placement of a sensor in that position, are referred to as sensors.
The excitation signal is a 5 cyclic square burst with a centre frequency of 80 kHz. The recorded signal is filtered with a digital bandpass filter 12. order with the lower and upper limit of 60 kHz and 100 kHz respectively.

2. Distance Prediction Methodology

The goal is to evaluate the capability to predict the distance of a damage based on the information of one single actuator-sensor-path. The signal that is available for this is a time signal at the sensor position in a pristine structure state and a second on after a damaged was induced. In the signal processing several features are computed for each of five time windows. With these features a regularized multiple linear regression machine learning approach is carried out. The dataset is split into 80% trainings and 20% test data.

2.1 Features

In the signal processing features are calculated based on the pristine plates time signal (SP) and the damaged plates time signal (SD). The calculated features are grouped into three categories, based on whether and if so, how the signals interact with each other.
In first group there are standalone features, which are only considering one signal. In the second group (comparing features), features are calculated by the ratio of a characteristic of the two signals and in the third group the two time signals interact directly with each other. The definition of each feature studied is listed in the following (formula 1 – 10).

Standalone features:

- Energy of single signal: $ESS_{SP} = \sum_{i=1}^{n} SP^2$ (1)
- Maximal value: $MAX_{SP} = max(|SP|)$ (2)
- Index and value of maximum value: $\mathrm{PxT_{SP}} = i_{MAX\_SP} \cdot MAX\_SP$ (3)
- Standard deviation of the Hilbert transformed signal: $StDe_{SP} = \sqrt{\frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{n-1}}$ (4)
- Skewness of the Hilbert transformed signal: $Sk_{SP} = \frac{n\,\Sigma_{i-1}^{n}(x_i-\bar{x})^3}{(n-1)(n-2)\left(\sqrt{\frac{1}{n-1}\Sigma_{i-1}^{n}(x_i-\bar{x})^2}\right)^3}$ (5)
- Kurtosis of the Hilbert transformed signal: $Kurt_{SP} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2\right)^2}$ (6)

With i_{MAX_SP} being the index of the maximal value, x_i value of the $\mathrm{i^{th}}$ point in the time signal, $\bar{x}$ the mean value of the time signal and n the number of data points in the time signal.
The standalone features are calculated for the pristine state (SP) as well as the damaged state (SD).
Comparing features:
The comparing features are calculated for each standalone feature by taking the ration of the pristine and the damaged state features twice: once dividing the pristine standalone feature by its damaged state counterpart and once dividing the smaller value standalone feature by its higher value counterpart.
In addition to this the Signal Amplitude Peak Squared Percentage Differences is calculated with:

$$SAPS = 1 - \left(\frac{MAX_{SP} - MAX_{SD}}{MAX_{SP}}\right)^2. \quad (7)$$

Directly comparing features:

- Pearson Correlation Coefficient:

$$CC = \frac{\sum_{i=1}^{n}(SP \cdot SD) - \sum_{i=1}^{n} SP \cdot \sum_{i=1}^{n} SD}{\sqrt{\sum_{i=1}^{n}(SP^2) - (\sum_{i=1}^{n}(SP^2))^2} \cdot \sqrt{\sum_{i=1}^{n}(SD^2) - (\sum_{i=1}^{n} SD)^2}} \quad (8)$$

- Signal Sum of Squared Differences:

$$SSSD = 1 - \frac{\sum_{i=1}^{n}(SP - SD)^2}{\sum_{i=1}^{n} SP^2} \quad (9)$$

- Ratio of Covariance Matrix Eigenvalues: the ratio of the Eigen values (λ) of the covariance matrix (2x2 by definition) between the pristine and the damaged state signal:

$$RCME = 1 - \frac{\lambda_{SD}}{\lambda_{SP}}. \quad (10)$$

Each feature is calculated for different time windows, aimed to cover one wave interaction event each. Additionally, the whole signal is also defined as a time window. The time windows are the same for every signal. The time windows are described in the Table 1. The different wave interaction events are shown in Fig. 2.

Table 1. Overview of the arriving wave package interactions

Time window	***Description of wave package***
1	Arrival of S0 directly from piezo
2	Arrival of A0 from the mode conversion at the damage

3	Arrival of A0 directly from piezo
4	Arrival of A0 scattering at the damage
5	Whole signal

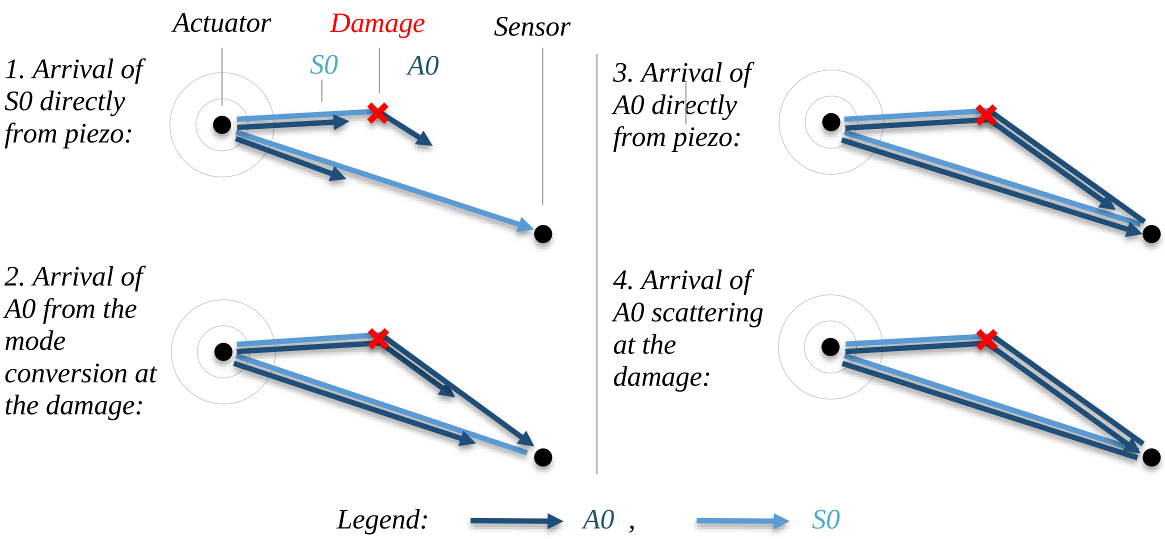

Fig. 2. Sketch of time window events

2.2 Multiple Linear Regression

The machine learning algorithm multiple linear regression is used, to weight all features to predict the shortest distance between the direct actuator-sensor-path and the centre of the damage. It is trained on 80% of the experimental data and 20% is used to validate the prediction process. The order of the dataset is randomised before it is split; the features are normalised.
The regularised training is done according to formula 11, with θ being the features coefficients, X a matrix of all features and y the minimal distance to the direct path. The two datasets are the training and test dataset (X_{train}, y_{train}, X_{test}, and y_{test}).

$$y = \theta_0 + \theta_{F_1} \cdot x_{F_1} + \theta_{F_2} \cdot x_{F_2} + \cdots + \; +\theta_{F_n} \cdot x_{F_n} = \theta \cdot X \tag{11}$$

The features coefficients (θ) are calculated analytically via normal equation (formula 12). λ is the regularization term and chosen as 0.1.

$$\theta = (X_{train}^T \cdot X_{train} + \lambda \cdot E)^{-1} \cdot X_{train}^T \cdot y_{train} \tag{12}$$

$y_{prediction}$ is the predicted minimal distance to the direct path based on the trained features coefficients and the test feature dataset (formula 13). $error$ (formula 14) describes how far the prediction of the minimal distance is off of the actual minimal distance y_{test} and will be used to evaluate the prediction.

$$y_{prediction} = \theta \cdot X_{test} \tag{13}$$

$$error = y_{test} - y_{prediction} \tag{14}$$

3. Results: Distance Prediction Capabilities

In order to evaluate the capability of this process in predicting the distance between a damage and the direct actuator-sensor-path, this section will showcase the results of the described process and compare it to the established way of using one feature, which represents a damage in an elliptic area around the actuator-sensor-path [6–8].

3.1 Established Method: Damage Index

To display the information obtained by this established method the value, called damage index (DI), of one feature is displayed at its sensor's positions. The chosen feature is defined in such a way, that a value of one or close to one represents that there is a high probability of a pristine plate state. A value of less than one represents an increasing probability of a damage. The lowest possible value is zero.
In order to not list all of the possible damage indices one correlation-based index is chosen (Correlation Coefficient (CC)) and one based on the energy arriving at the sensor position (Energy Ratio (ER)). These are displayed for two time windows (TW). Firstly, the time window of the A0 mode wave package directly arriving from the actuator and secondly the time window of the A0 mode arriving from the initial A0 mode scattering at the damage. The direct A0 mode is chosen to showcase the damage recognition sensitivity. For the Correlation Coefficient (CC) (Fig. 3, a) there is a small sensitivity directly in the shadow of the damages, but as expected almost none next to the damages, as this is in a time window of the direct arrival of this wave package. The Energy Ratio (ER) (Fig. 3, b) has a similar behaviour, but with a higher sensitivity and less "no damage" detections directly in the shadow of the damage.

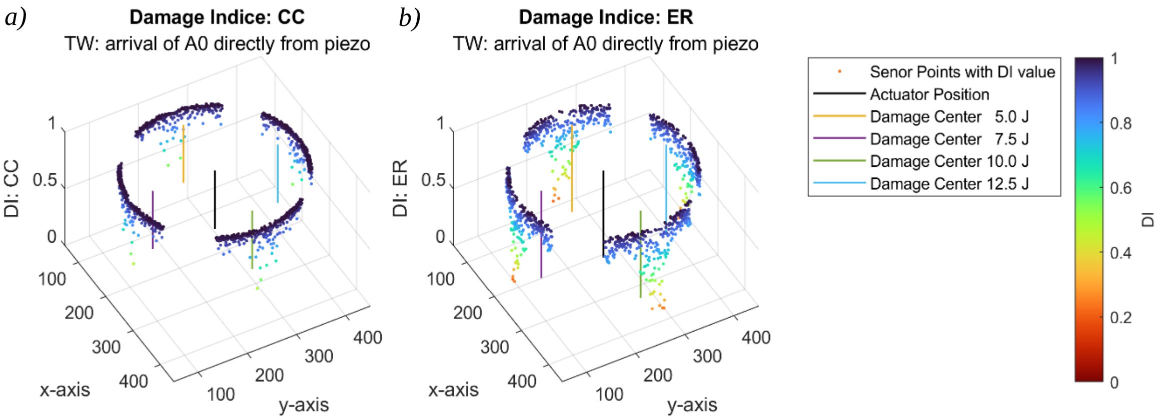

Fig. 3. Single Damage Index damage sensitivity of the arriving A0 wave package coming directly from the actuator, using a) the Correlation Coefficient (CC) and b) the Energy Ration (ER)

Fig. 4 display the results of the two features in the time window of the A0 mode arriving from the initial A0 mode scattering at the damage. It is noticeable, that there is neither linear correlation between the distance of the damage to the direct actuator-sensor-path, nor, that there is a clear tendency of any kind between the location of the sensor and the feature values.

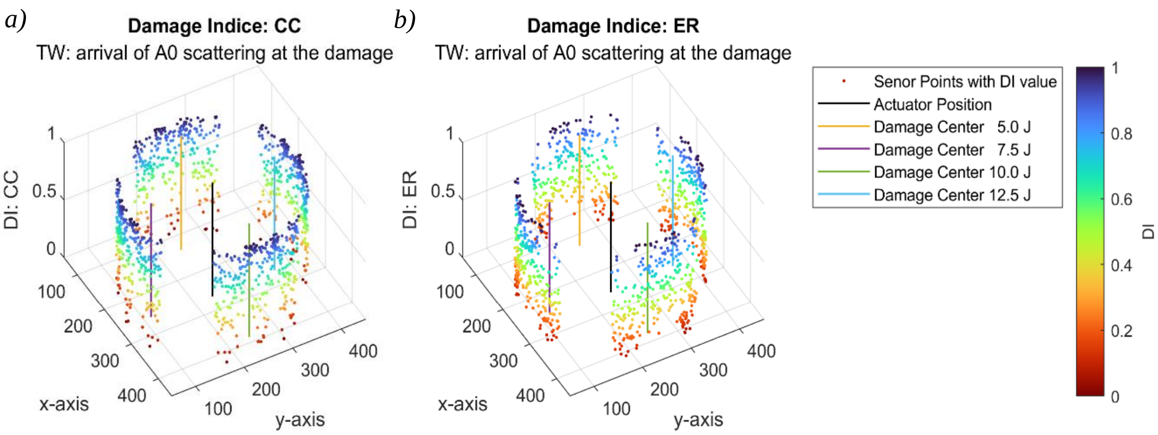

Fig. 4. Single Damage Index damage sensitivity of the arriving A0 wave package scattering at the damage, using a) the Correlation Coefficient (CC) and b) the Energy Ration (ER)

3.2 Distance to Damage Predicting Process

In the distance to damage prediction process multiple information of one time signal are taken into account to achieve a sensitivity besides the direct path and therefore being able to perform the prediction. For this the time signal is separated into several time windows representing different wave events arriving at the sensor. For each of these time windows various characteristics are calculated to serve as features for a machine learning operation.
To now compare the capabilities of this distance prediction process to the established way of using one feature, the prediction accuracy is calculated. For this, the whole dataset was randomly divided into a training and a test dataset. The size of the 20% test set is data of 222 actuator-sensor-paths represented by the described features. The evaluation is based on the prediction error, which is calculated by subtracting the actual distance from the predicted one (formula 14).
The standard deviation of the error shall be used as the quality criterion of the process. The smaller the standard deviation of the error of the test set, the more accurate the prediction and therefore the better the developed process. As the test dataset only consists of 222 paths the standard deviation will fluctuate depending on which paths were randomly chosen to be used as the training dataset and which ones to predict. Therefore, the number of predictions is increased by randomly defining the training and test dataset multiple times and keeping track of the errors on every repetition. This way it is possible to calculate a value for the accuracy of the system which is decoupled from a single random dataset drawing. In the Fig. 5 the result of 500000 predictions shows how accurately the process predicts the distance from a damage to the direct actuator sensor path, based on of a single paths signal.

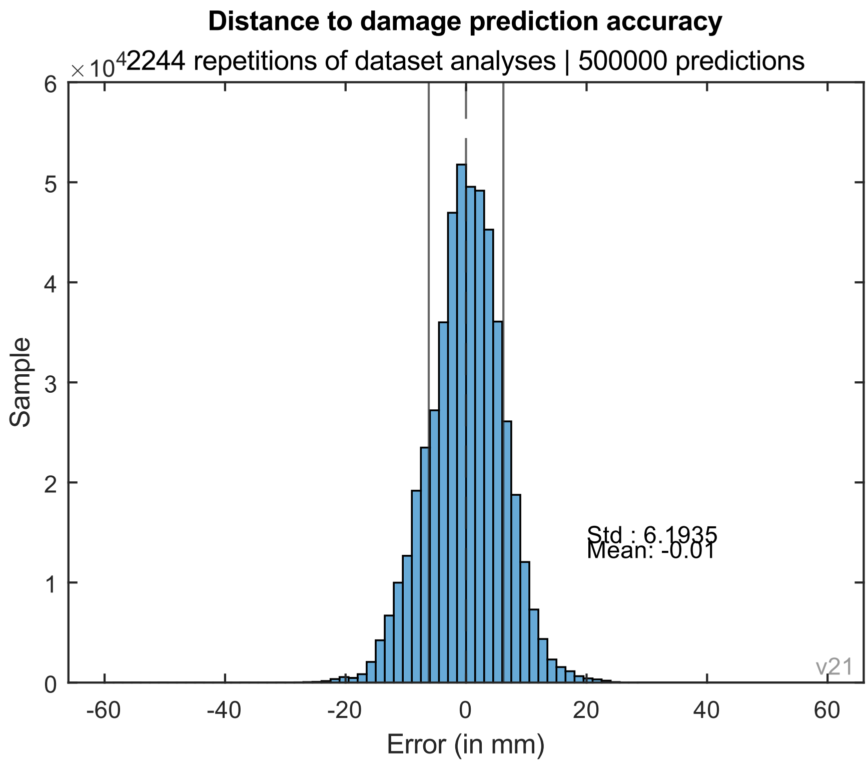

Fig. 5. Distance to damage prediction accuracy of 500000 predictions

4. Conclusion

The results described in this paper showcase the capabilities of the proposed method of predicting the distance of a damage to the direct actuator-sensor-path as well as an established way of using the time signal of a single path to locate damages.
In the established method of using a single feature to predict a damage in the region of the actuator-sensor-path, it is observed that no reliable sensibility of a single feature outside of the damage shadow is possible. In contrast, it could be shown, that a feature-based distance estimation is indeed possible. A standard deviation of under 7 mm in predicting the damages distance, shows that a single path can give a geometric information of the location of the damage. Thinking about the combination of multiple paths in a structural health monitoring network this offside path distance prediction shows a promising step into an accurate damage localisation with probability reconstruction algorithms.
Also, the prediction process provides a tool to evaluate the quality of parameters in structural health monitoring. One can study different features and can evaluate those based on the standard deviation of the error. It is the same with other process parameters like the regularisation or the time windows.
Furthermore, it has to be discussed, what effects the double use of information has (referring to the comparing features as well as using the whole window on top of the wave event-based windows). A more in-depth study of this and the features relevance is needed.

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