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Acoustic Emission-Based Diagnosis Using AlexNet: How Wave Propagation Effects Classification Performance

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Abstract. Composite materials are frequently used due to light weight and high stiffness. However, the use of composite materials is limited due to several micro-mechanical damage mechanisms, which are currently not well understood. Therefore, Acoustic Emission (AE) is frequently suggested for in-situ diagnosis of composite materials in Structural Health Monitoring. Elastic stress waves in the ultrasound regime are recorded using highly sensitive measurement equipment. Based on suitable analysis and interpretation of the waveform data, different micro-mechanical damage mechanisms such as delamination or fiber breakage can be distinguished. Frequently, data-driven approaches are suggested for classification of AE data. In literature, attenuation of AE due to wave propagation is currently the main limiting factor in AE-based diagnosis. In particular, AE is strongly attenuated in composite materials due to dispersion as dominant attenuation mechanism. Furthermore, depending on the source location, which is usually not known a-priori, different propagation paths are obtained in practice. Therefore, the effect of wave propagation on AE is important and can not be neglected to achieve reliable classification. However, the effect of different propagation paths on the classification performance is often not considered explicitly. Due to dependence of wave propagation behavior on waveform characteristics (e.g. frequency), it can be expected that the impact of wave propagation on AE classification performance depends also on the related source mechanism. Therefore, it is worth to study how classification performance of different source mechanisms is effected by wave propagation. In this paper, the dependence of the classification performance on different propagation distances is experimentally investigated in detail. To achieve highly reproducible AE measurements, different artificial AE sources are induced using surface mounted piezo elements. The corresponding waveforms are measured at two different locations. For classification, a convolutional neural network-based classification scheme is established. The pre-trained AlexNet architecture is fine-tuned using measurements obtained using different excitation signals. The classification performance is evaluated with particular focus on the impact of wave propagation. The variations in propagation distance have a strong impact on the classification performance. As main conclusion for AE-based SHM it can be stated that variations in the propagation path should be considered. Furthermore, the underlying source mechanisms should be taken into consideration for reliable performance estimation.

Introduction

Acoustic Emission (AE) refers to ultrasound stress waves, which are released from localized sources in a loaded material. Using suitable measurement equipment, AE waveforms can be recorded in-situ and used for diagnosis [1]. Regarding Structural Health Monitoring (SHM) of

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composites, the use of Acoustic Emission (AE) is frequently suggested to distinguish between different micro-mechanical damage mechanisms such as delamination, matrix crack, debonding, and fiber breakage [1]. Typically, thin structures such as coupon specimens and plates are used as specimen geometry. Due to the geometry, ultrasound stress waves propagate in two fundamental modes. Using advanced signal processing and interpretation, different damage mechanisms can be distinguished. For instance, digital filtering was suggested for mode separation in [2] and [3]. According to Martinez-Jequier et al. [3] delamination could be identified using modal analysis of AE, whereas additional consideration of the frequency spectrum was necessary to distinguish between the remaining damage mechanisms.

Due to the complexity of AE interpretation, data-driven approaches are frequently suggested for AE-based diagnosis of composite materials. These include e.g. different clustering techniques [4], Support Vector Machine [1], and neural networks [5]. A comparison of modal AE analysis and neural networks is presented by McCrory et al. [5]. In principle, the results of both methods are in in good agreement. However, it was stated as an advantage of data-driven approaches that AE data can be classified into more than two classes [5]. Furthermore, the use of frequency and time-frequency domain transformations is of particular importance for classification of AE. It is well known that – compared to classical AE parameters, which are extracted in time domain – peak frequencies are less sensitive to different experimental conditions. For instance, Beheshtizadeh et al. [6] concluded that wavelet transform is superior for the analysis of AE signals because highly detailed representation is obtained especially regarding weak signal components.

In literature, attenuation of AE due to wave propagation was identified as main limitation of AE-based SHM. Different approaches were suggested to compensate the effect of wave propagation, e.g. correction of AE parameters by calibration experiments [7]. However, according to Maillet et al. [8], high frequency components are attenuated stronger and lower values of the frequency centroid are obtained at increasing propagation distance. Furthermore, Asamene et al. [9] pointed out that mode- and frequency-dependent attenuation may have an effect on AE signatures. Moreover, Kharrat et al. [10] reported additional distortion of AE waveforms due to damage accumulation within the material. Also, an effect of external load on the attenuation of AE in a composite plate could be demonstrated in [11]. However, while data-driven approaches are frequently suggested in context of AE, the impact of changes in the propagation path is often not considered explicitly.

In this paper, the dependence of the classification performance on propagation distance is investigated in detail. Particular focus is given to the difference between symmetric and asymmetric wave modes. To achieve highly reproducible AE measurements, different artificial AE sources are induced using surface mounted piezo elements. The remainder of this paper is structured as follows. In Section 2, the experimental setup and the classification scheme using AlexNet architecture are explained in detail. In section 3, experimental results are presented. This includes detailed discussion of the induced AE and the effect of wave propagation on the classification performance for each of the wave modes. Finally, the main conclusions are summarized.

Methods and materials

The experimental setup is illustrated schematically in Fig. 1. As specimen geometry, a thin plate is chosen, which is a typical specimen geometry for testing of composite materials. The specimen is manufactured from CFRP material and has dimensions of 800 x 800 x 1 mm^3. In principle, two fundamental modes propagate in this geometry, which are the symmetric (S0) and

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asymmetric (A0) mode. Wide specimen dimensions are chosen to reduce the effect of edge reflections. As AE transducers, Piezoelectric Wafer Active Sensors (PWAS) are bonded to the top and bottom surface of the plate. To obtain reproducible waveforms with defined modal content at the sensors, AE transducers are sometimes used in active mode [10]. Here, AE is induced using two active PWAS, as suggested by Su and Ye [12]. The active PWAS T1 and T1b, which are oriented face-to-face through the material, are driven by a frequency generator. Here, windowed sine bursts with 6 cycles at a frequency of 100 kHz are used. By choosing in-phase or out-of-phase excitation of the active PWAS, the dominant mode of propagation can be controlled precisely.

As sensors, PWAS T2 and T3 which are located in a distance of 100 mm and 200 mm from the excitation, are used. Additionally, two PWAS T2b and T3b are bonded face-to-face at the opposite surface of the plate to verify the modal content of measured waveforms. A similar sensor arrangement was used for instance by Martinez-Jequier et al. in [3] to assess the modal content of AE waveforms. The AE waveforms are recorded continuously at a sample rate of 4 MHz. Each excitation burst is triggered by an external signal, which is also recorded for post-processing.

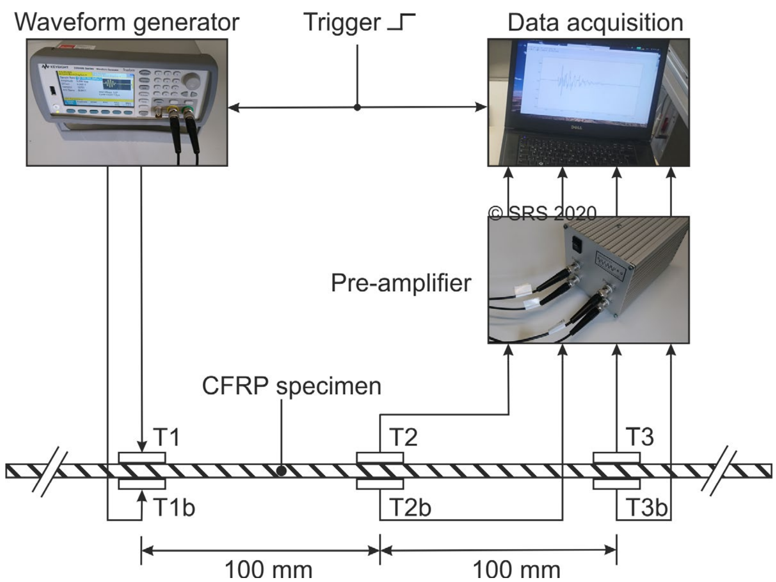

Fig. 1. *Illustration of the experimental setup (Chair of Dynamics and Control, U DuE, Germany).*

Recently, deep learning, which emerged from the field of image classification and computer vision, received significant attention in SHM literature [13]. High classification performance can be achieved with sophisticated neural networks. However, due to the large number of parameters in deep neural networks, training is computationally intensive and a large amount of data is necessary. Therefore, transfer learning is frequently suggested if the amount of training data is limited. One approach to transfer learning is fine-tuning of pre-trained networks [13]. While most of the parameters of trained neural networks – or parts of trained neural networks – are used as initial values, only specific parts of the network are modified. Here, fine-tuning refers to additional training of the modified network with a new dataset. The advantages of using pre-trained networks are that fine-tuning is usually faster, requires less data, and can be realized using a regular desktop computer.

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The AlexNet is a Convolutional Neural Network architecture, which was proposed by Krizhevsky et al. [14]. Today, AlexNet is frequently used for transfer learning. For instance, Dorafshan et al. [15] compared the performance of edge detectors, which is an image processing-based approach, and AlexNet for image-based crack detection in concrete. According to the results, improved performance can be achieved using AlexNet architecture. Furthermore, best performance was achieved using fine-tuning as compared to full training of the network. Furthermore, Hemmer et al. [16] suggested a transfer learning approach for classification of faults in rolling element bearings based on vibration and acoustic emission measurements and concluded that fine-tuning of AlexNet scales well to multiclass problems.

The original AlexNet architecture comprises five convolutional layers (conv1 - conv5) and three fully connected layers (fc6 - fc8). For transfer learning, the architecture is usually modified so that it is suitable for the new classification problem. Hemmer et al. [16] replaced the final classification layer to fit the desired number of classes. Lu et al. [17] replaced the last three layers. Additionally, the learning rate can be adapted to focus parameter updates mainly on the modified layers during training, as suggested in [16]. In this paper, the final layer of the architecture is adapted for classification into 4 classes. The modified architecture of the AlexNet is illustrated in Fig. 2. Furthermore, the learning rate of the fully connected laser is increased by a factor of 20 to reduce the impact of training on the parameters of the convolutional layers. During fine-tuning, stochastic gradient descent with momentum algorithm was used with the following settings: initial learning rate: 1e-4, mini batch size: 10, validation frequency: 20.

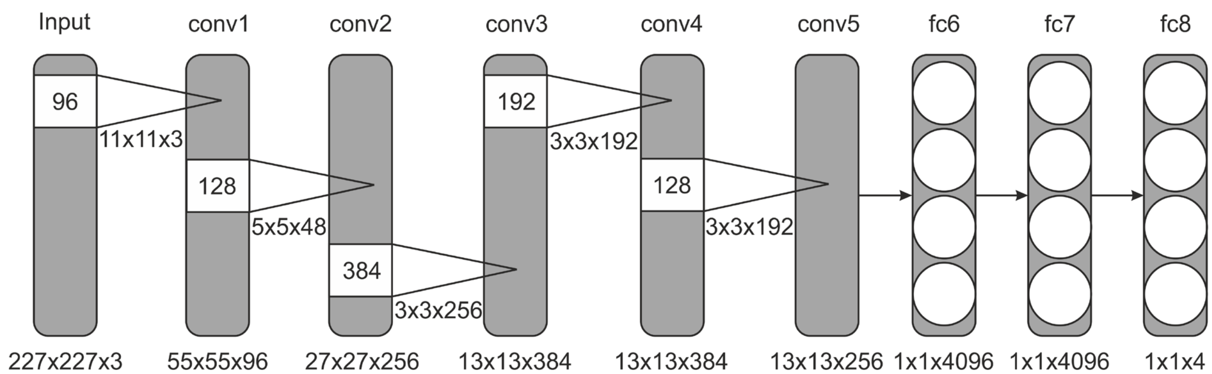

Fig. 2. *Simplified illustration of modified AlexNet architecture.*

Experimental results

In this section, different classes of artificially induced AE signals are presented. Each AE waveform is measured at two different locations. Furthermore, preprocessing of the waveform data is explained. Finally, classification performance is evaluated in detail. Particular focus is placed on how the classification performance is effected by changes in the propagation path.

To verify the procedure, which was used to induce AE in the plate specimen with defined dominant mode, the modal content of resulting AE measured by the sensors is assessed. To this end, measurements of the two sensors T2 and T2b, which are located face-to-face at the top and bottom surfaces of the plate, are used. Symmetric and asymmetric modes can be separated by adding and subtracting the responses of the sensors at the top and bottom surfaces of the plate, respectively, as suggested in e.g. [3]. From the responses presented in Fig. 3, dominant S0 and A0 mode are observed depending on (a) symmetric (in-phase) and (b) asymmetric excitation (out-of-phase). To investigate the effect of wave propagation on the classification performance, a dataset was recorded comprising AE waveforms with dominant S0 and A0 modes of different

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intensity. By choosing different excitation signals, AE waveforms with different modal content were induced. For classification, the waveform data were transformed into frequency domain using continuous wavelet transform. As input to the classifier, images of 227x227x3 are used. Examples of each class are presented in Fig. 4.

Subsequently, AlexNet is used for classification of different AE waveforms. To demonstrate that in principle it is possible to distinguish between waveforms, which are related to different excitations, training and test data are chosen from the same sensor. In each case, a total of 400 samples are used during training and 200 samples during test.

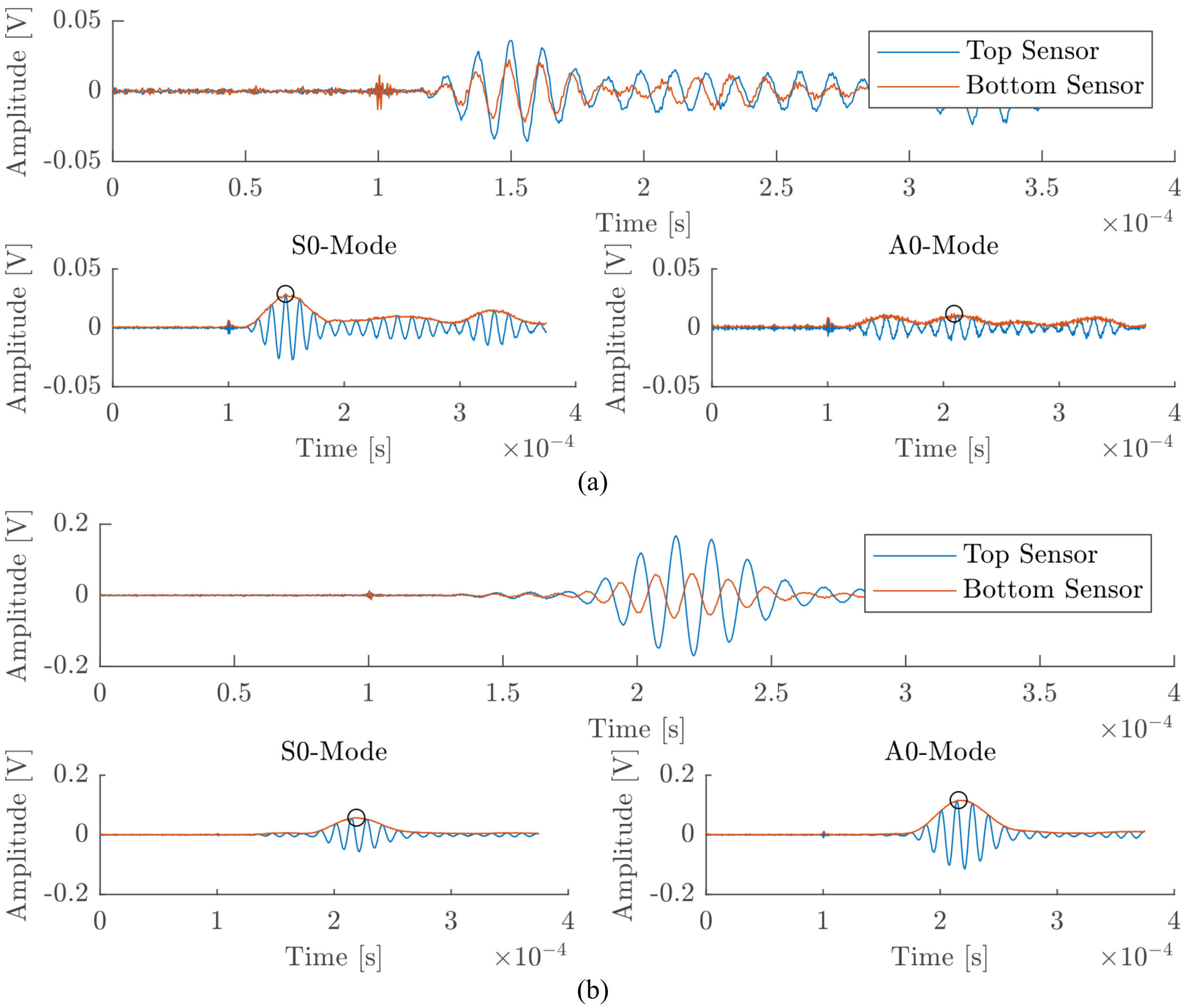

Fig. 3. *Artificially induced AE with dominant symmetric (a) and asymmetric (b) mode.*

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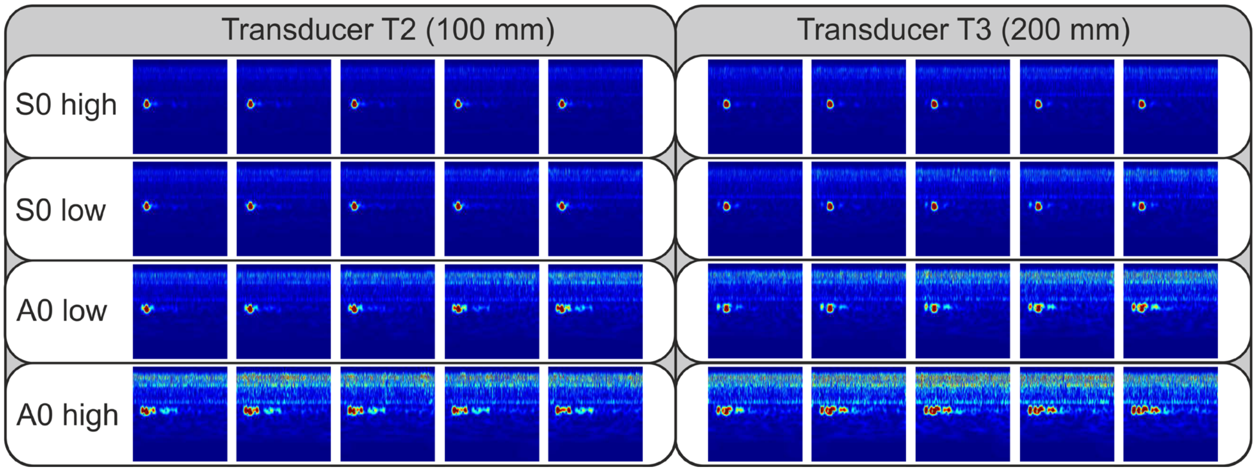
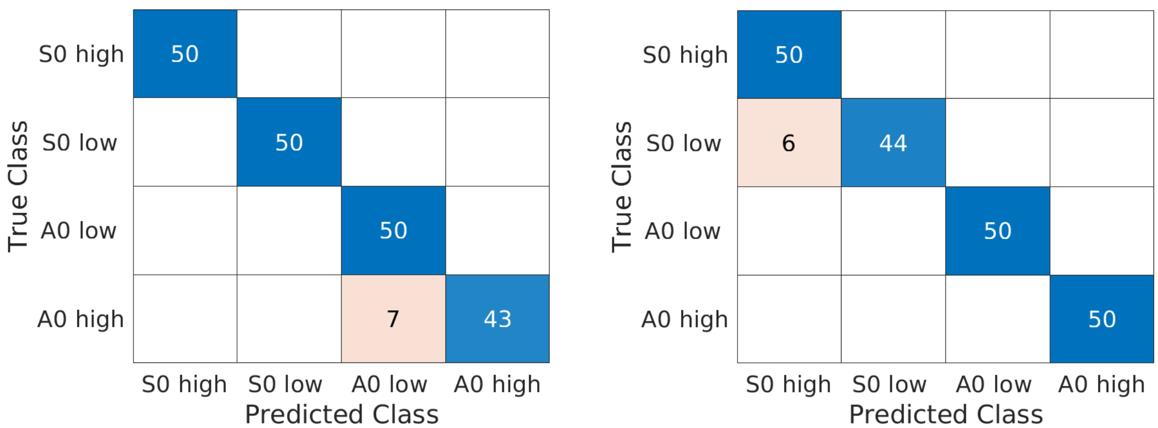


Fig. 4. *Scalograms of AE waveforms at sensor T2 (left) and sensor T3 (right).*

In Fig. 5, the confusion matrices showing test results for the data from the sensors T2 and T3 are presented. In general, good performance of the classifier is achieved and different AE, which are related to symmetrical and asymmetrical excitation, can be distinguished reliably.



(a) (b)

Fig. 5. *Confusion matrices for (a) sensor T2 and (b) sensor T3.*

Finally, the effect of changes in the propagation distance on the performance of the classifier is investigated. To this end, two different cases are considered: (i) the initial propagation distance is increased after training and (ii) the initial propagation distance is decreased after training. Here, data from different sensors were used during training and test. In each case, a total of 400 samples are used for training of the AlexNet. For test, 200 samples are chosen from the other sensor. The corresponding confusion matrices are shown in Fig. 6. It is obvious that the classification performance degrades due to the change in the propagation distance between training and test. However, it is notable that symmetric and asymmetric wave modes are effected differently. In Fig. 6 (a), most of the classification errors are related to asymmetric excitation whereas classification of AE related to symmetric excitations is more difficult in Fig. 6 (b).

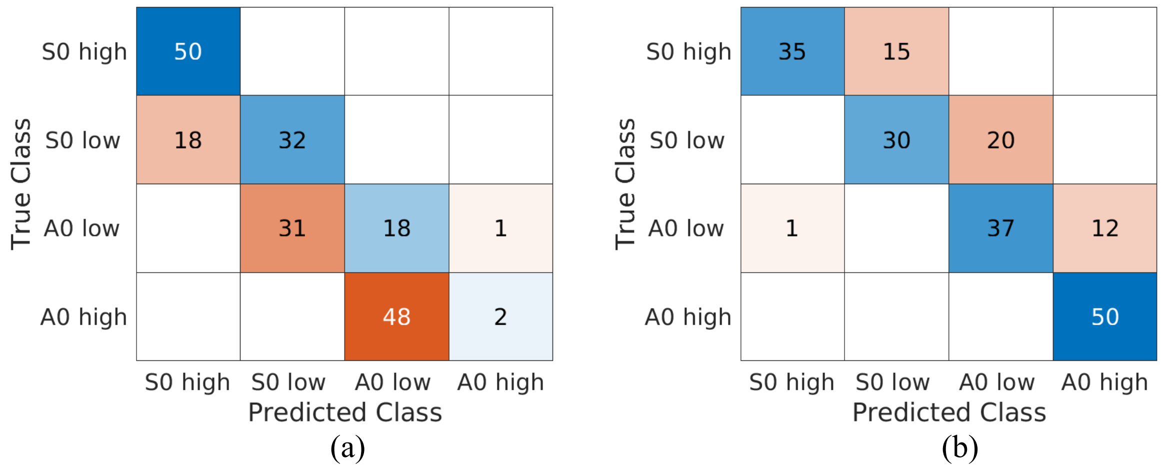


Fig. 6. *Confusion matrices for (a) Training: T2, Test: T3 and (b) Training: T2, Test: T3.*

Similarly, the effect of changes in the propagation distances on the classification performance for both excitations can be observed using cross validation. In Fig. 7, results of 5-fold cross validation are presented. Here, recall is reported to assess the performance for each class. In accordance with the previous results, better performance can be achieved for asymmetric excitations if the propagation distance is increased between training and test. If the propagation distance is reduced between training and test, the performance of the classifier is better for symmetric excitations. Therefore, it can be concluded that the effect of different propagation distances on the classification performance depends also on the underlying source mechanism.

Fig. 7. *Cross validation results.*

In this example, AE signals with dominant symmetric and asymmetric wave mode were chosen, which are in practice related to e.g. fiber breakage and delamination, respectively [2]. It could be shown that in principle, the classification performance at different propagation distances depends on the corresponding wave mode. However, the effect of wave propagation on the classification performance may be different depending on frequency of AE signatures and dispersion characteristics of the material.

Summary and conclusion

In this paper, a detailed investigation regarding the impact of variations in the propagation distance of AE in composite material on the classification performance is presented. A thin plate is chosen, which is a typical specimen geometry. Artificial AE sources are induced using PWAS transducers, which allows to precisely control the modal content of the AE signals. For classification, a transfer learning approach – i.e. fine-tuning of pre-trained AlexNet architecture – is used. Particular focus is given to the performance of the classifier for AE waveforms with different dominant modes.

The variations in propagation distance have a strong impact on the classification performance. In particular, two different cases in which the propagation distance is i) increased and ii) reduced between training and test. Here, the effect on the classification performance also depends on the dominant wave mode of AE. Therefore, as main conclusion for AE-based SHM it can be stated that variations in the propagation path can not be neglected, also if frequency domain features are used. The robustness of a classifier to variations of the propagation path depends on the dominant mode of the AE waveforms. The underlying source mechanisms should be taken into consideration for reliable performance estimation.

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