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ABSTRACT

INDEX TERMS Digital filter limits, gear damage, linear prediction, signal processing, vibration analysis

I. INTRODUCTION

The formation structural damage is increasingly a problem in several areas. For example, aging processes or growing damage on bridge structures can lead to dramatic consequences [1]. If components such as girders fail, it can even lead to the collapse of such a structure. The formation of cracks is not only a problem in infrastructural buildings. Fatal structural damage can also occur in equipment such as pressure vessels, gas cylinders or liquid containers. To monitor the occurrence and progression of such cracks or structural damage, acoustic emission analysis can be used as a structure health monitoring method. Here, sensors are used to record structure-borne sound events that occur and assign them to a cause, such as the formation of a crack [2]. Investigated in the field of structure health monitoring are not only buildings [3] and pressure vessels [4], but also technical processes [5], electrotechnical elements [6], geological phenomena [7] or tribological processes [8]. Besides these, several important fields of acoustic emission and structural health monitoring are discussed in [9]. With the increasing interest in structure health monitoring, the demand for localization of cracks or structural damage is also growing. This applies especially to very large geometries such as bridges, water tanks or pipes, where repairs of damaged subcomponents are considerably cheaper than exchanging the entire structure. There are already many approaches for the localization of acoustic emissions. Overviews of these can be found in [10], [9]. The approaches for the localization of passive acoustic emissions can be divided into the modal acoustic emission method, beamforming, triangulation and artificial neural networks. Since the modal acoustic emission is based on the separation of the A_0 and S_0 modes according to the Lamb wave description [11], prior knowledge about the geometry and the occurring signal frequencies is necessary for the calculation. Precise sensor positions are required for localization via beamforming or triangulation. In addition, for most methods a precise estimation of the arrival time is necessary [12]. This is not possible in many real applications due to unwanted signal components (e.g. ambient noise). The localization via artificial neural networks provides the advantage that neither prior knowledge about the geometry, the material nor the sensor position is necessary, due to the fact that all relevant properties are learned by the network. The disadvantage of localization via neural networks, on the other hand, is the necessary appropriate database for training. In [13] a localization of pencil lead breaks via a two-stage back-propagation network is presented. Here, the network is trained with the arrival signal times. Based on the different arrival times at different sensor positions a localization is performed. In [14], localization via a neural network based on differences in signal propagation times on a carbon-fiber-reinforced polymer pressure vessel is presented. Using arrival time difference between waves as input data, a significantly better localization can be achieved compared to conventional signal processing methods. In addition to using differences of signal travel times as input data, in [15] a vibration signal is passed to a neural network. The localization of the pencil lead breaks is realized here using an autoencoder in combination with a softmax layer. Localization via CNNs and spectrograms of the vibrational signals is presented in [16]. Once again, pencil lead breaks are used as a source for localization. The examples shown demonstrate that neural networks have already achieved very good results for the localization of acoustic emissions. However, previous applications have focused primarily on localizing acoustic sources such as pulses or pencil lead breaks under laboratory conditions without ambient noise. This is usually not the case in real applications, since in almost all structure health monitoring applications there are many unwanted signal components that need to be handled. In contrast to this, the following contribution presents a localization via a CNN based on spectrograms, which localizes anomalies in a disturbed environment.

II. CONCLUSION

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