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Inverse determination of elastic material parameters from ultrasonic guided waves dispersion measurements using Convolutional Neuronal Networks

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Introduction

In the context of Industry 4.0 and especially in the field of Structural Health Monitoring, Condition Monitoring and Digital Twins, simulations are becoming more and more important. The exact determination of material parameters is required for realistic results of numerical simulations of the static and dynamic behavior of technical structures. There are many possibilities to determine elastic material parameters. One possibility of non-destructive testing are ultrasonic guided waves. For the evaluation of the measurement results, mostly inverse methods are applied in order to be able to draw conclusions about the elastic material parameters from analysing the ultrasonic guided wave propagation. For the inverse determination of the elastic material parameters with ultrasonic guided waves, several investigations were carried out, e.g. the determination of the isotropic material parameters through the point of zero-group-velocity [1] or anisotropic material parameters with a simplex algorithm [2]. These investigations are based on the evaluation of dispersion images. Machine learning and in particular Convolutional Neural Networks (CNN) are one possibility of the automated evaluation from image data, e.g. classification or object recognition problems. This article shows how the dispersive behavior of ultrasonic guided waves and CNNs can be used to determine the isotropic elastic constants of plate-like structures.

Concept

For using supervised learning algorithms and CNNs, a diverse data set of dispersion images with known material parameters is required. For this reason, the Scaled-Boundary-Finite-Element-Method (SBFEM) [3] is used to generate synthetic data and create dispersion images comparable to real measurement results, as it is shown in Figure 1. The dispersion images are computed using a 2D Fast Fourier Transform of the surface displacement take along a line simulated with the SBFEM to calculate the Frequency and Wavenumber. Python with the software framework Keras from Tensorflow is used to implement the CNN and train the model on the dispersion images to predict the isotropic elastic material constants.

Data and Preprocessing

For generating dispersion images using the SBFEM, random elastic material parameters are used in the range of 0.2 to 0.45 for the Poisson's ratio and for the Young's modulus normalized to density in the range of $26 * 10^6 [m^2/s^2$ to $28 * 10^6 [m^2/s^2]$ which includes various metallic materials like aluminum or steel. The generated dataset contains 1000 labeled samples which are converted into 8 bit gray scale images with a resolution of 656x875 pixels. For training a neuronal network a normalization of the input and output data is recommended. Therefore, each pixel is normalized into the value range zero to one, dividing by 255. The material parameters, which the CNN is predicting, are also normalized into the range from zero to one by applying a normalization related to the minimal and maximum value. For evaluating and training the model, the dataset is split into 600 training, 300 validation and 100 test samples.

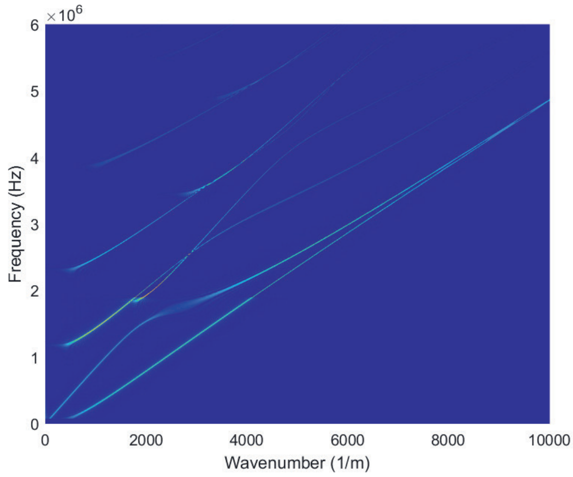

Figure 1: A dispersion image obtained using the SBFEM

Architecture

For the baseline architecture, a simple feed forward CNN architecture as usually used for classification problems is chosen and applied to the regression problem. The structure of the 2D convolutional layers is the same in each layer, only the number of filters doubles for each layer. The filter kernel size is always three by three and step size of the kernel is one in every direction, as well as the dilation rate. This is intended to prevent information loss, as is the use of "same padding" in the border area of the images while applying the kernel. The initial values of the kernel are initialized using the Keras "$glorotuniform$" method. The biases are initialized to zero and no regularizers are applied to biases or kernels. Due to the regression problem and the normalization of the input and output, a ReLU activation function is used in each layer. To downsize the feature map while processing, max pooling with a two by two filter size and step size of two is applied. The sequence of these layers remains the same and is repeated several times until the transition to the decision layer. A short summary is listed in Table 1. The transition between the last convolutional layer and the fully connected layers is done by a flattening layer. The hyperparameters of the fully connected layers are equal to the convolutional layers. A separate model is trained for predicting Poisson's ratio and density-normalized Young's modulus separately, while the architecture is the same for both models.

Table 1: Summary of the baseline model architecture

Layer (type)	Output Shape	Param
conv2d	(None, 656, 875, 16)	160
activation	(None, 656, 875, 16)	0
max pooling2d	(None, 328, 437, 16)	0
	...	
max pooling2d 5	(None, 10, 13, 1024)	0
conv2d 6	(None, 10, 13, 2048)	18876416
activation 6	(None, 10, 13, 2048)	0
flatten	(None, 266240)	0
dense	(None, 1)	266241
activation 7	(None, 1)	0

Number of trainable parameters: 24,549,761

Training

For training of the model only Keras functions are used. The Adam Optimizer ($beta1 = 0.9$, $beta2 = 0.999$, $epsilon = 1 * 10^{-7}$) with the mean squared error (MSE) as a loss function. Due to the normalization of the output data, the loss function is called the normalized MSE (NMSE). The batch size is set to 5 for a general result considering there are only little changes in the behavior of the dispersion curves for different material parameters. The training data is shuffled every epoch to avoid learning from sequences. The learning rate is initialized to 0.0001 and regulated using the ReduceLROnPlateau callback function($monitor$ = ”$valloss$”, $factor = 0.1$, $patience = 10$, $verbose = 1$, $mode$ = ”min”, $mindelta = 0.0001$, $cooldown = 5$, $minlr = 0$). The training is carried out for 50 epochs and the best model achieved up to then is saved for each epoch. To achieve reproducible results a random seed and some environment parameters are fixed.

Results

First results for the mean absolute error (MAE) of the testdata and the percent error of the testdata related to the maximum value of the simulation are shown in Table 2. These first results for the testdata are based on the model which achieved the best result for the validation data during training. The best result on the validation data for Poisson's ratio was achieved in the 30th epoch and for the density-normalised Young's modulus in the 40th epoch. These first results show that a good prediction of the elastic material parameters is possible. As expected, the error for predicting values close to min and max of the range of values is higher than for values which are in the mid-range of the simulated material parameters, as is the error of the test data compared to training- and validation data.

Table 2: Test results for the baseline model.

Dataset	Test	
	MAE	Percent
Poisson's ratio	$9,56 * 10^{-4}$	0,027%
Young's modulus/density	8842,16	0,032%

For further evaluation of the CNN, the Grad-CAM Algorithm, which is normally used for classification methods, is applied to ensure that the neuronal network is predicting from the behavior of the curves. Figure 2 shows that the area of low wavenumbers and frequencies has a higher influence on the calculation of the Poisson's ratio.

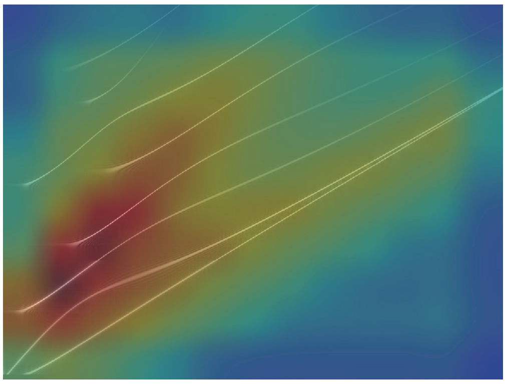

Figure 2: A ”heat-map” for predicting the Poisson's ratio calculated using the Grad-CAM Algorithm

Summary

This article shows that it is possible to extract material parameters from the dispersive behavior of guided waves using SBFEM simulation data and Convolutional Neuronal Networks. In future studies, this method could be extended to the determination of anisotropic material parameters and other arbitrary boundary parameters from real measurement dispersion images.

References

[1] Dominique Clorennec, Claire Prada, and Daniel Royer. Local and noncontact measurements of bulk acoustic wave velocities in thin isotropic plates and shells using zero group velocity lamb modes. *Journal of Applied Physics*, 101(3), 2007.

[2] Manuel Webersen, Sarah Johannesmann, Julia Düchting, Leander Claes, and Bernd Henning. Guided ultrasonic waves for determining effective orthotropic material parameters of continuous-fiber reinforced thermoplastic plates. *Ultrasonics*, 84:53–62, 2018.

[3] Hauke Gravenkamp, Carolin Birk, and Chongmin Song. Simulation of elastic guided waves interacting with defects in arbitrarily long structures using the scaled boundary finite element method. *Journal of Computational Physics*, 295:438–455, 2015.