Optimal Frequency selection for vibration based damage detection using pattern recognition

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Abstract
Damage detection methods of structural components have been extensively evaluated in theoretical and experimental research studies in the last few years. As the research objectives for structural health monitoring (SHM) are broadly diversified, this study focuses on the signal interpretation techniques. The acquired data from a sensor network should be optimally evaluated in consideration of environmental effects. In this context, pattern recognition techniques are widely used to evaluate the health state of structures from acquired data. This work assesses the dependency of various excitation frequencies in guided-wave based SHM and the performance of damage detection. As a result, a solution for an efficient and optimized signal interpretation model is provided. The needed vibration response to detect damage states is applied by a piezoelectric sensor network, which is used to apply guided-waves through the structure and to measure the vibration response. Finally, the pattern recognition approach is evaluated experimentally using beam and sandwich structures to expose differences in the frequency domain. The important outcome of this study is to improve the efficiency and performance of SHM systems by optimizing the excitation frequency using pattern recognition approaches.

1. INTRODUCTION

The research field of structural health monitoring (SHM) describes the way to state the structural integrity. In this context, it is important to optimize the capability of sensor networks by applying intelligent interpretation systems. These intelligent systems predict the health state based on acquired data in a real-time environment [1]. This study combines a piezoelectric sensor network, guided-wave based analyses and machine learning to create an adaptable damage detection routine [2, 3].

In recent research projects structural health monitoring finds its application in various fields ranging from civil to aerospace structures. The research objectives are broadly diversified, which are all addressing the improvement of SHM technologies. One focus for damage detection lies in the research of signal interpretation techniques, because the acquired data should be optimally evaluated in concern of environmental effects. In addition to that, the SHM system should be capable to deal with a big database and to evaluate the data in real-time. In this context, machine learning algorithms are commonly used to evaluate the health state of structures. Machine learning can be directly used in SHM applications including environmental effects (noise, imperfection, statistical tests, etc.) to train a new system and to solve the inverse problem.
2. PIEZOELECTRIC TRANSDUCERS

The sensor network to investigate the structure contains multiple lead zirconate titanate (PZT) elements. Based on the piezoelectric effects, these elements will be either used as sensor (direct piezoelectric effect) or actuator (converse piezoelectric effect). The direct piezoelectric effect occurs by applying a normal or shear stress to the structures, which will result in an electric charge. Furthermore, an applied electric field results in additional strains. The piezoelectric effects were discovered by the brothers Pierre and Jacques Curie in 1880 and 1881 [5, 6]. As an electro mechanical constitutive relation this can be defined as

\[
D = d^d \sigma + e^\sigma E \quad (1)
\]

\[
\varepsilon = S^E \sigma + d^E E \quad (2)
\]

where \( D \) is the electric displacement, \( e^\sigma \) is the dielectric permittivity, \( \varepsilon \) is the strain vector, \( S^E \) is the elastic compliance, \( \sigma \) is the stress vector, \( d^d, d^E \) are the piezoelectric coefficients and \( E \) is the electric field [7]. For further calculations, we assume isotropic piezoelectric material and all PZT elements are polarized in the direction of \( x_3 \) axis, which results in the following electro-mechanical constitutive relation:

\[
\begin{bmatrix}
\varepsilon_1 \\
\varepsilon_2 \\
\varepsilon_3 \\
\varepsilon_{23} \\
\varepsilon_{31} \\
\varepsilon_{12}
\end{bmatrix} =
\begin{bmatrix}
S_{11} & S_{12} & S_{13} & 0 & 0 & 0 \\
S_{13} & S_{22} & S_{23} & 0 & 0 & 0 \\
S_{31} & S_{32} & S_{33} & 0 & 0 & 0 \\
0 & 0 & 0 & S_{44} & 0 & 0 \\
0 & 0 & 0 & 0 & S_{55} & 0 \\
0 & 0 & 0 & 0 & 0 & S_{66}
\end{bmatrix}
\begin{bmatrix}
\sigma_1 \\
\sigma_2 \\
\sigma_3 \\
\sigma_{23} \\
\sigma_{31} \\
\sigma_{12}
\end{bmatrix} +
\begin{bmatrix}
0 & 0 & d_{31} \\
0 & 0 & d_{32} \\
0 & 0 & d_{33} \\
0 & d_{15} & 0 \\
d_{15} & 0 & 0 \\
0 & 0 & 0
\end{bmatrix}
\begin{bmatrix}
E_1 \\
E_2 \\
E_3
\end{bmatrix}. \quad (3)
\]

This constitutive relation gives the correlation between induced strain \( \varepsilon \), the applied stress field \( \sigma \) and the applied electric field \( E \).
3. GUIDED WAVES

To evaluate the health state of structures, guided waves are applied and measured by the sensor network. The waves will propagate as transmitted strains through the structure and any change in the local stiffness, crack, or delamination (composite structures) will cause reflection, dispersion, attenuation and mode shape change [8]. In this study, the guided wave is generated as tone burst by modulating a sine wave including the Hanning Window. This option is chosen to create a narrow banded frequency spectrum, which is less dispersive compared to a classical sine wave [8]. The corresponding wave function reads

\[ y(t) = -\frac{A}{2} \sin \left( \frac{2\pi f_c t}{\text{cyc}} \right) \left( 1 - \cos \left( \frac{2\pi f_c t}{\text{cyc}} \right) \right), \]  

(4)

where \( A \) is the Amplitude, \( f_c \) is the centre frequency and \( \text{cyc} \) is the number of cycles of the tone burst. In the example that is shown in Figure 2, we have a centre frequency of 20 kHz, 3.5 cycles and after Fast Fourier Transformation, a narrow banded frequency spectrum will be obtained.

![Figure 2: Tone burst with 20kHz centre frequency and Hanning Window in time (left) and frequency (right) domain.](image)

In the next step, the wave response in each sensor is characterised by the existence of local minima and maxima. Any change based on a damaged structure or loading condition will affect the wave response. Furthermore, the wave response will be used to identify the applied frequency from the actuator as a test for sufficiency. This feature confirms the trained model, any non-agreement between applied and measured wave frequency reports an unknown/untrained loading or damage condition. Therefore, every frequency agreement leads to a predicted damage state.

4. SUPPORT VECTOR MACHINE

The support vector machine (SVM) is one of the most popular approaches for off-the-shell supervised learning [3]. This method constructs a maximum margin separator that acts as a decision boundary to separate the acquired data in different classes. The separating hyperplane can be used to classify linear or high-dimensional spaces using different kernels. So, it is also possible to separate a nonlinear data space. In this context, different damage states will be classified (including a non-damaged structure) and used for training. Furthermore, the variation of the applied frequencies and the damage location are conducted for the training process. Every class can then be described as

\[ \theta_0 + \theta_1 f_1 + \theta_2 f_2 + \ldots + \theta_n f_n \geq 0, \]  

(5)

where \( \theta \) is the trained parameter and \( f_i \) is the used kernel to classify the data. In this study, a Gaussian kernel is used, which can be described as follows:
Before a dataset can be classified, it is necessary to start the training process for the SVM, which can be assumed as a black box with its inputs $x_i$ and outputs $y_i$. During the training, the parameters $\theta$ will be optimised to show the best relation between $x_i$ and $y_i$. Therefore, the success of training for machine learning techniques results from a good database, which is then used to train and evaluate the SVM. In this context, the extracted input features from each measurement give the information about peak height and peak location of the wave response, which is measured by each sensor. The supervised learning algorithm also needs labeled data. This labeled data is the system output $y_i$ and is specified by the information of the applied frequency and the damage state of the structure. All informations for training and evaluation of the SVM are taken from simulation and experimental measurements.

5. **BEAM AND SANDWICH STRUCTURE**

This study contains two different models. The first fundamental research analyses the behaviour of a beam element, while the second model illustrates a sandwich structure. Both models are implemented in a FEM simulation and experimental specimens are built up.

![Beam element with attached piezoelectric elements.](image1)

![Sandwich structure with attached piezoelectric elements.](image2)
The beam element is shown in Figure 3 and has the dimensions of 45mm x 5mm and a thickness of 1.5mm. This element is made of an AlCuMg1 alloy (EN AW 2017A) and is equipped with 4 piezoelectric elements, which will be used to generate the wave and measure the wave response as well. The beam is only fixed to one side in the simulation and experimental setup. Furthermore, the actuator for the wave excitation is always chosen to be next to the clamped end, while the other three PZT elements are only used for sensing.

In addition to the beam element, a sandwich structure is built up (Figure 4). This sandwich structure is composed of a surface layer on each side and a core material. The surface layers have the same geometrical and physical attributes as the beam element, which has been described before. In addition to that, the sandwich structure consists of a closed-cell core material ROHACELL® 71 HERO. This core material is 5mm wide, 45mm long and 10mm thick.

The different damage states will be implemented by drilling a hole in the beam element as well as in the upper layer of the sandwich structure. The location and size (hole diameter) of the damage will vary in order to produce a diverse database.

6. RESULTS

After introducing the concept of piezoelectric transducers, guided-waves and support-vector-machines, the results will be split up into two steps. In the first step, the results of the general guided-wave concept will be presented, followed by the comparison between beam and sandwich structures. The second step will be based on the evaluation of the trained SVM to predict the health state of a given structure.

In Figure 5, the guided-wave is shown at different time points, which also relates to the simulation of the beam element. The clamped side is located on the upper left part of each figure. Furthermore, the wave excitation starts at the PZT element located next to the fixed side and propagates through the structure and the attached PZT elements, which are sensing the wave response.

In addition to the simulation, Figure 6 shows the difference between the beam and sandwich structure in the experimental study. The measurement for the beam element shows a highly disperse wave response, which results from the slender structure. On the other side, the wave response of the sandwich structure is less dispersive and the wave packets can be determined from the figure. The higher thickness of the sandwich structure results in a stiffer structure in comparison to the beam element. In this context, the stiffness of structures affects the duration until the wave is completely degraded, which can also be obtained in Figure 6 and described as the damping influence.

For the next step, the complete database of sensor responses will be separated into training and cross-validation sets. Thus, the performance of the trained SVM has to be evaluated to return the efficiency of the SVM and the database. The database should be carefully chosen, because it can lead to overfitting or other problems, which will not be discussed in this study [3].
In this context, the score is calculated for the database to evaluate the SVM performance. Every new data point of the cross-validation set will be evaluated with the help of the score function to analyse the classification based on the trained SVM. Any disagreement in the predicted class will lead to a bad score, while good prediction will lead to a maximum score of 100%.

In the proposed method, a very good score can be obtained using piezoelectric transducers, guided-waves and the SVM to classify the data. Even for a small database, the SVM achieved a score over 90%, which can be easily improved by extending the database for new damage classes.
7. CONCLUSION

The proposed method for damage detection combines three different research fields. The result can be evaluated by calculating the score of the trained SVM, which is an indicator for the accuracy in the cross-validation set to display the efficiency of the proposed method. In our results, we obtain even for a small dataset a score over 90%. This can be easily improved by taking into account environmental effects (e.g. temperature) and different loading conditions. Furthermore, the extracted features confirm the expected predictions and show good results for the boundary hyperplane. In this work, we proposed a 2-step-way to identify the applied frequency and damage states in structures. The obtained results are trustable and can be easily extended to more damage classes.

REFERENCES