Damage Detection in Piping Systems Using Pattern Recognition Techniques

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ABSTRACT

The interest in the propagation of ultrasound waves in pipe-like solid waveguides arises out of several areas of the structural health monitoring (SHM) community for the detection, localization and assessment of defects as well as the prediction of remaining life in civil, mechanical, aeronautic and aerospace structures. SHM premise offers a continuous observation of the structural integrity of operational systems. This is particularly convenient, therefore, for the reduction of time and cost for maintenance without decreasing the level of safety. Some practical applications are the monitoring of pipework in gas and oil industries, suspension bridge cables, nuclear fuel cladding tubes, etc.

This paper describes an approach for SHM using guided waves in pipe-like structures in terms of a pattern recognition problem. The formalism is based on a distributed piezoelectric sensor network for the detection of structural dynamic responses. Several methods for signal filtration, feature selection and extraction, and data compression of the recorded time histories are discussed and evaluated. Principal Component Analysis (PCA), Non-Linear PCA (NLPCA) and Wavelet Transform are among them. Additionally, the different clusters, corresponding to each damage level are visualized with the help of Self Organizing Maps (SOM). Tests were performed on a piping system where the properties of the proposed methods are compared and appraised with experimental pitch-catch signals between the pristine and the damaged structure.

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INTRODUCTION

Cylindrical Structures can be found in a variety of technical applications. Piping systems, composed of interconnected hollow cylindrical structures, can be found on ground, maritime, and aerial structures. For economic and safety reasons, their structural integrity has to be secured in order to prevent high class damages. Continuous observation is therefore desirable but in many cases hard to achieve [1]. Ways of reliable and appropriate inspection have been a field of research for long time. At the beginning, vibration-based techniques were developed for global monitoring [2]. On a more local level, conventional non-destructive testing (NDT) methods based on ultrasonic waves have been applied by well-trained craftsman. Due to possible inaccessibility as well as due to the high costs, still a vast quantity of critical cylindrical structures is monitored only within long intervals or not at all. As a consequence, wave-based techniques rapidly evolved due to their well-known properties and were adapted to the concept of SHM. These techniques enable the recording of baseline measurements in order to relate changes in the signals to structural damage and allow the monitoring of complex structures [3]. Recent years have shown new developments in ultrasonic generation techniques and sensors [4-5]. Ultrasonics have been successfully applied to analyze the interaction of guided waves with discontinuities in pipes [6]. Concerning passive techniques, Acoustic Emission has been used as a method of leakage detection [7]. From the various types of sensors used, piezoelectric sensors and fibre optics have shown to be most suitable for structural integration. With reference to the efficient use of data, data compression, feature extraction and feature selection from dynamic measurements, several methods have been established in the field of condition monitoring and SHM. Using time series as basis, a series of suitable steps for achieving PCA for evaluation are explained in [8]. Advanced techniques of data compression and evaluation can be found in [9], explaining the analysis with the help of nonlinear components using a multilayered perceptron architecture with an auto-associative topology as well as with discrete wavelet transformation. This paper presents a study of intelligent signal processing techniques for the purpose of structural damage detection and classification on the basis of a pattern recognition procedure. A brief theoretical background of wave propagation in hollow cylinders and the feature extraction methods used here are presented for completeness. At the end, several linear and nonlinear methodologies for data mining are applied and evaluated for experimentally gained data, and their advantages and disadvantages are discussed for their application into SHM systems.

THEORETICAL FOUNDATION

Waves in Hollow Cylinders

Guided waves in hollow cylinders were first studied by Gazis [10]. It is known that the solutions of the equations of motion for hollow cylinders lead to three different classes of propagating modes (see Rose [11]). These tube modes are designated as longitudinal, torsional and flexural modes. Three fundamental modes are depicted in Figure 1 for a frequency of 180 kHz, an outer radius of 20mm and 2mm thickness.

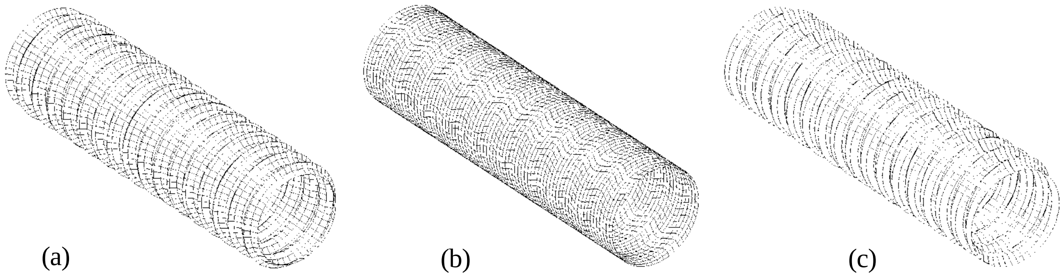

Figure 1. Comparison of the different mode shapes for hollow cylinder made of stainless steel: (a) Longitudinal L(0,1), (b) Torsional T(0,1) and (c) Flexural F(0,1) at 180kHz.

Dispersion curves were calculated using a general-purpose computer program developed by the authors [12] and depicted in Figure 2. Just the fundamental modes are labeled.

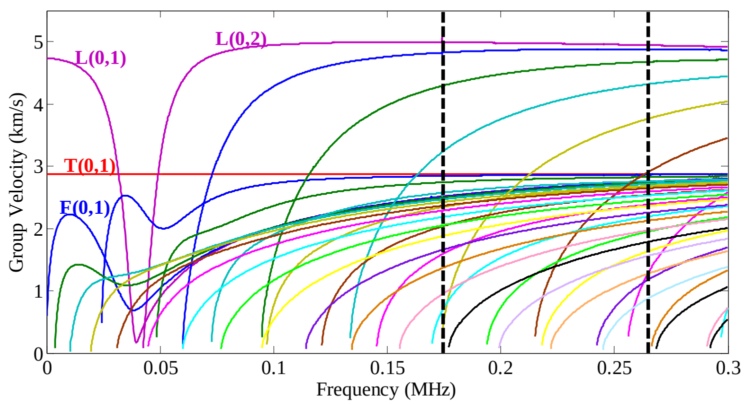

Figure 2. Group Velocity at a given frequency band for different modes.

From Figure 2 can be observed that the wave propagation phenomenon is much more complicated than that of a plate. This is given by the fact that many more modes exist in a pipe than in a plate of similar thickness and this effect makes the interpretation of the signals difficult. There are a total of 40 modes in the frequency range up to 300 kHz. The vertical dashed lines enclose the frequency band where good signal to noise ratio was obtained for the experiments conducted in this study.

Feature Extraction and Damage Indicators Methods

Several ways for feature extraction and calculation of damage indicators are evaluated in this study. In the time domain field, the application of PCA on unfolded time histories from dynamic responses collected at different sensor positions can be used to extract features relating the linear correlations between these responses. According to Mujica [8], the use of a limited number of principal components is sufficient to evolve data analysis. PCA is a classical method of multivariate statistics and its theory and use are documented in many textbooks [13]. If nonlinear correlations between variables exist, non-linear mapping methods could describe the data with higher precision and/or by fewer components than PCA. In the present study, a multilayer perceptron network with auto associative topology is implemented for non-linear mapping purposes [14]. Time-frequency analysis can also be used to study the time variations of the dynamic responses in spectral characteristics. One possible approach is the use of wavelet transformation. There exists a vast amount of literature related to wavelet applications for damage identification. The discrete wavelet transform (DWT) on the basis of the two-channel subband coding scheme as proposed by Mallat [15] was applied to the recorded dynamic responses. Each wavelet coefficient represents time and frequency information of the regarded signal. The optimum number of level decompositions was determined based on a minimum-entropy decomposition algorithm. Daubechies wavelets were chosen for this study. Moreover, the calculated coefficients can be used for further processing with the afore mentioned mapping methods. These methods are mainly used for the distinction of damaged and pristine state, helping to execute novelty detection. To visualize the results of the process of data analysis it is possible to calculate a damage indicator e.g. using T^2 or Q statistics and Outlier Detection. Also presented here is the visualization with the help of self-organizing maps [16]. They compress high dimensional data on a low dimensional display. Either data of the pristine structure are chosen for training and distance to the map exhibits the damage indicator or all data are taken to process the map. In this case the distance between the different parts of the map shown in the U-matrix, which evaluates the space between neighboring nodes of the map, can be used as indicator of separation between different groups. Further details can be found in [17].

PRACTICAL IMPLEMENTATION

Experiments were carried out to investigate the practical performance of the techniques discussed in the previous section. Figure 3 depicts the experimental setup used for testing. The pipe work was made of steel and the piece which should be monitored is fixed stationary at both ends with four screws. It has a diameter of 40 mm with a wall thickness of 2 mm and a length of 850 mm. On both sides of the pipe behind the flanges, four piezoelectric elements are mounted equally distributed around circumference and rotated 45° compared to the screws in the flanges.

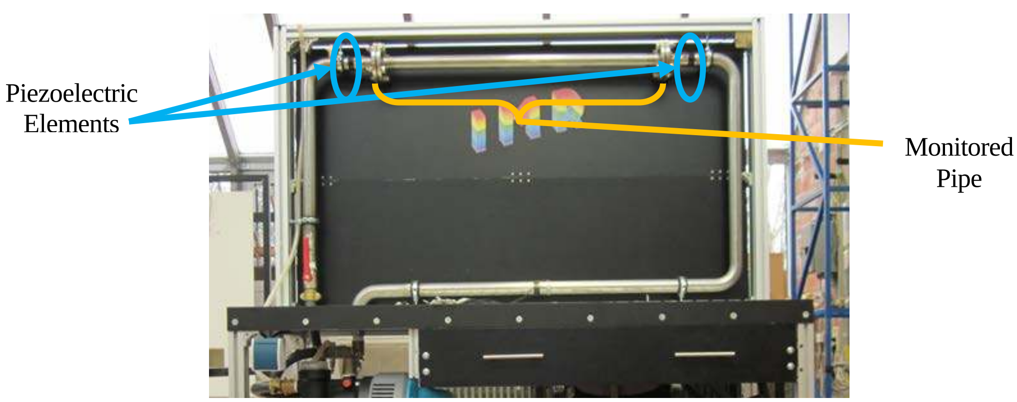

Figure 3. Experimental Setup.

Damage was introduced into the structure in several steps. It was executed as a cut with an angular grinder. The depth and its vertical extension are enlarged in four steps, starting with a cut of 0.75mm depth. This cut is increased in depth in a second step until the wall is almost penetrated, followed by an increase in vertical direction.

Finally the pipe's wall is penetrated, increasing depth in the middle of the former notch.

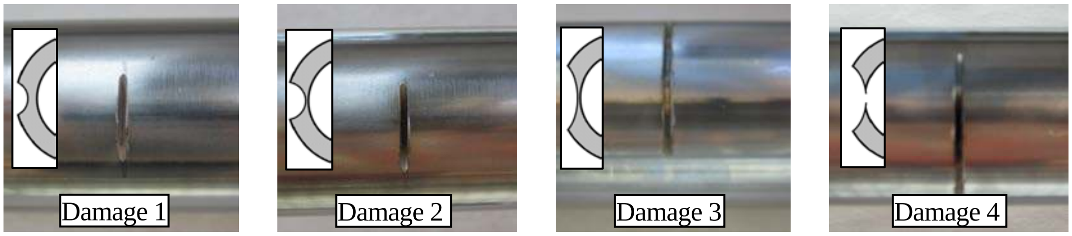

Figure 4. Different damage steps: Damage 1 - Damage 4 and its cross sections.

The different states can be found in Figure 4. The transducers were excited by a Hann-windowed toneburst voltage signal with a carrier frequency of 180 kHz and 5 cycles in order to construct the data base for the pristine as well as all the damaged cases. The signal is penetrating through both flanges and the pipe and recorded by the sensors at the other side of the pipe.

EXPERIMENTAL RESULTS

Examination of the results in time domain shows the high similarity of the signals taken at different levels of damage indication.

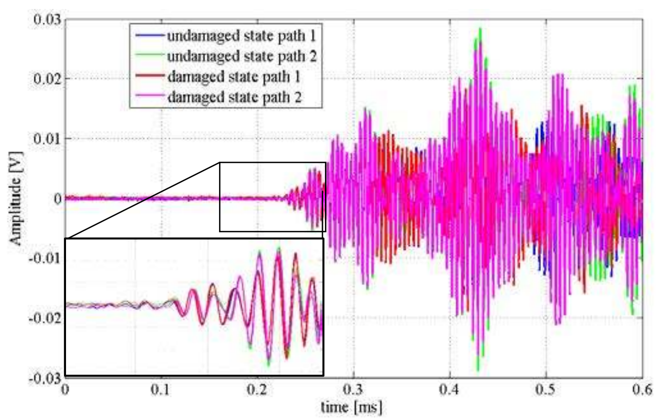

Figure 5. Recorded Data of two different paths for undamaged and damaged states in time domain.

Figure 5 shows the data in time domain recorded from two sensor-actuator combinations with similar paths. The difference between these is larger than the differences between damaged and pristine state. For the analysis of the data the path from actuator 1 to sensor 5 was chosen, when only taking into account one path and unfolding the data of the paths to all sensors otherwise. The processing of the data with the help of mathematical tools reveals more information than pure time data does. The analysis as described in the theoretical part with the help of linear PCA shows, that damage can be separated from pristine state only using the first three components of the PCA. On a 3D-plot almost all groups can be distinguished (Figure 6 a – next page).

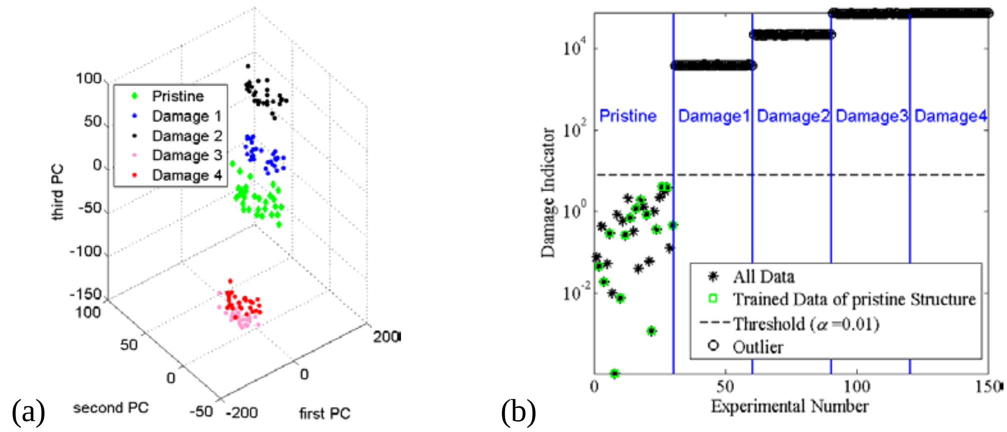

Figure 6. (a) First three PCs from linear PCA of all damage types and the pristine structure (b) Damage indicator calculated by outlier analysis using the first three components of PCA.

Nevertheless data gained form a relatively small damage reveals bigger distance to the data of the pristine structure than other data of the damaged structure does and the direction of distance is not the same for different damage sizes. This distance can also be used as basis for multivariate outlier analysis [18] making the distinction between damaged and undamaged state possible. However, the different damages 3 and 4 cannot be clearly separated, even when taking more PCs into account (Figure 6 b).

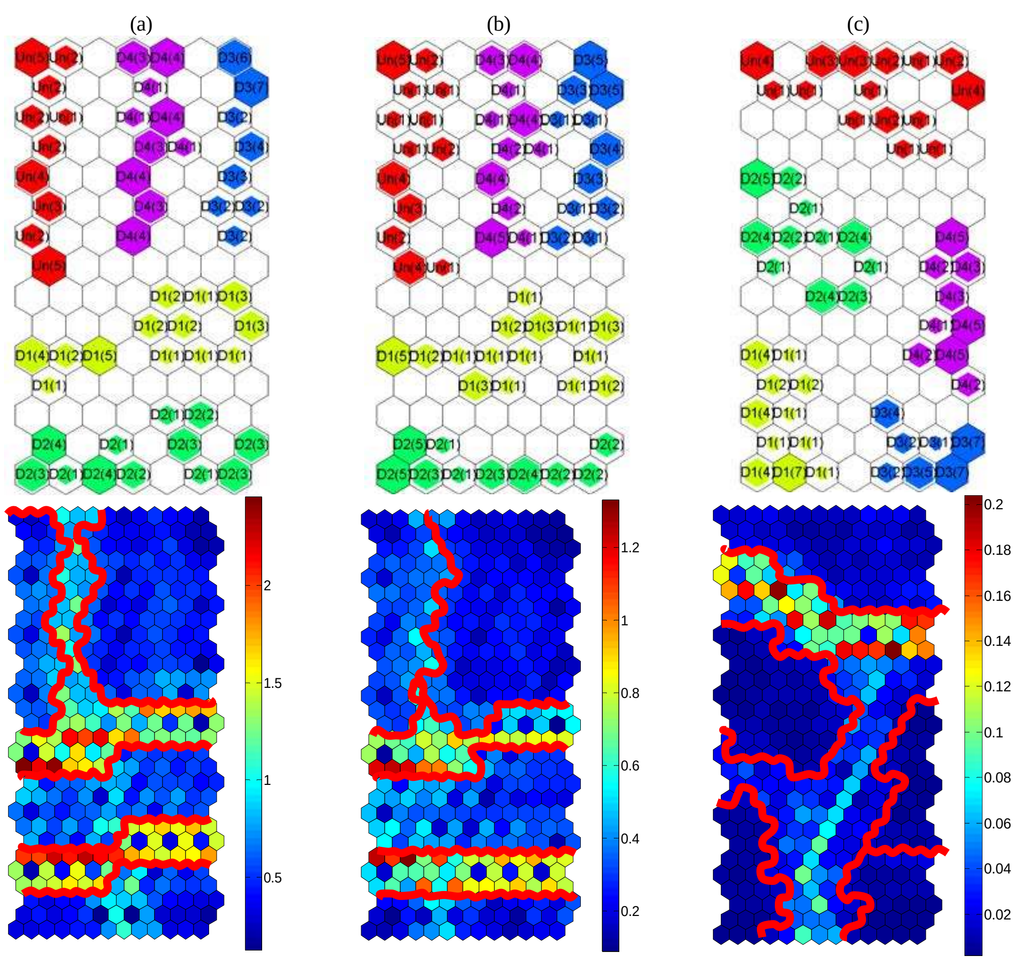

Figure 7. SOMs (first row) and U-Matrices (second row) for unfolded Data (Actuator 1): (a) 17 PCs using PCA, (b) 11 PCs using DWT and (c) 4 PCs using NLPCA.

When using Self Organizing Maps for the visualization of the PCs employing more components, the different damage sizes can be distinguished, but the U-matrix as an indicator of the separation does not show significant borders between the groups. Using the unfolding of the data, this can only be changed partly (see Figure 7a). Using the method of DWT for the unfolded data does not lead to better results when using SOMs for the visualization. The advantage is that lower levels are given by a smaller number of wavelet coefficients. Damage detection is still possible separating the pristine from the damaged structure but the U-matrix shows a smaller separation between data of pristine and damaged structure for Damage 3 and 4, while the separation to damage 1 and 2 can be seen easily (see Figure 7 b). The utilization of Multilayer Perceptrons creating nonlinear components reveals a strong separation of the undamaged state from all damaged states. Nevertheless the different damage types can be separated showing the great advantage of the method chosen when highlighting that only 4 components were used to calculate the SOM (Figure 7 c). Still the differentiation between the last two damage types is only slightly shadowed, which leads to the assumption that these two do not differ in many ways.

CONCLUSION

The monitoring of hollow cylinders as an important task to increase security of piping systems is depending to a high rate on the modes activated in the monitoring process. Within this publication, an active damage detection method using piezoelectric elements is presented. Several methods for data evaluation are compared and evaluated using the time domain data collected from experiments. It can be seen that every method is able to distinguish between damage and undamaged state. The main difference resides in the computational cost and number of components that are required to reliably detect and/or classify damages. Nevertheless, this computational cost is just present during the construction of the model using the baseline data for the non-linear methods. The separation between the different damage types can be executed with the help of multivariate outlier analysis and PCA or SOMs and higher level processed data, with the limitation of not being able to distinguish damage 3 and damage 4 clearly. This results from the fact that the difference in damage severity is very small. It is also possible that the modes that were excited in the structure could not be able to interact with this slight change in damage depth. This is supported by the fact of the changing ratio of displacement and stress amplitudes along the wall thickness. During the experiments a shift of data could be seen, which was not desired and therefore the offset was subtracted. Further investigations might help to find the reason of these trends, changing from measurement to measurement. Moreover, the time data already shows a relation to the environmental conditions in the laboratory. To be able to use one of the methods mentioned above reliably, either a stable environment has to be secured or a way around this, including e.g. a temperature influence model needs to be developed.

ACKNOWLEDGEMENTS

The authors wish to thank Dr. Maxim Klinkov and Dr. Peter Kraemer as well as Mr. Wolfgang Richter and Mr. Gerhard Dietrich, who developed the test bed used here. Especially for taking part in performing the experiments, the authors would like to thank Fahit Gharibnezhad. The authors would like to express their gratitude to the Centre for Sensor Systems (ZESS) for sponsoring the research presented herein.

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