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Vibration-based structural health monitoring using large sensor networks

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Abstract. Recent advances in hardware and instrumentation technology have allowed the possibility of deploying very large sensor arrays on structures. Exploiting the huge amount of data that can result in order to perform vibration-based structural health monitoring (SHM) is not a trivial task and requires research into a number of specific problems. In terms of pressing problems of interest, this paper discusses: the design and optimisation of appropriate sensor networks, efficient data reduction techniques, efficient and automated feature extraction methods, reliable methods to deal with environmental and operational variability, efficient training of machine learning techniques and multi-scale approaches for dealing with very local damage. The paper is a result of the ESF-S3T Eurocores project "Smart Sensing For Structural Health Monitoring" (S3HM) in which a consortium of academic partners from across Europe are attempting to address issues in the design of automated vibration-based SHM systems for structures.

Keywords: structural health monitoring (SHM); vibration-based methods; sensor networks; machine learning; lamb waves.

1. Introduction

Optimal maintenance of civil engineering infrastructure will require a precise knowledge of its actual state of integrity and possible remaining lifetime. For many years, researchers have worked on global monitoring methods based on the analysis of the vibration signals of structures (Salawu 1997, Doebling *et al.* 1998, Alvandi and Cremona 2006, Montalvao *et al.* 2006), as an alternative to traditional, local monitoring techniques based on Non-Destructive Testing (NDT) inspection (Grandt 2003). Although a large body of the literature is devoted to the subject of vibration-based damage identification methods, industrial application of fully automated Structural Health Monitoring (SHM) systems are quite rare and usually confined to aerospace structures; the status of these systems is often "under development". Although the development of SHM has been concentrated around aerospace structures, there is a marked interest in transferring the technology into civil engineering. This transfer is anticipated to

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yield benefits commensurate with those gained in recent years by transferring general structural dynamic test technologies into the civil context. Technology transfer has not been trivial, it is a truism to say that civil structures present different problems to aerospace structures. The interest of the civil engineering research community in vibration-based SHM is reflected in the proliferation of special conference sessions and even entire conference series with a marked interest in the subject.[1] One example where SHM technology has made the transition to industrial practice is in the Acoustic Emission (AE) monitoring of pressure vessels (Scruby and Wadley 1982). Despite the promise of the AE methodology, the progress in developing appropriate instrumentation and computer disk storage has delayed transfer into the arguably more demanding aerospace context; however, progress is now being made (Paget *et al.* 2004). Although it is by no means an indicator of the widespread use of AE for civil structures, (Rippengill *et al.* 2003) at least illustrates the use of pattern recognition techniques in the interpretation of AE recorded from a bridge girder.

The modest objective of this paper is to illustrate some developments in more general SHM technology and also in the transfer of this SHM technology into the practice of engineering of civil infrastructure. The developments in question specifically arose as a result of the project “Smart Sensing for Structural Health Monitoring (S3HM)” funded within the framework of the ESF-S3T Eurocores program.

The Structural Health Monitoring (SHM) problem is usually seen as a four step procedure: (i) detection of deviation from a healthy state, (ii) localization of the possibly damaged areas, (iii) quantification of the damage and (iv) prediction of the remaining lifetime. There are two complementary aspects to a SHM system: (i) the hardware (sensors, transmission, signal processing), and (ii) the software (data mining, novelty detection, statistical analysis...).

While it is true to say that SHM technology has generated interest in the civil engineering research community; its use on real structures has so far been rather restricted, despite the fact that many bridges have recently been designed or retrofitted with substantial sensor networks. One might ask now, what has changed since the inception of such bridge monitoring systems; what are the new trends? One answer is that major improvements have been achieved in the hardware part of SHM systems, particularly those required for the lower-frequency environment of bridge vibration data. Most of the recent efforts have been spent on developing hardware solutions with new types of sensors (e.g., humidity, pressure, strain based on Fibre Bragg Grating Sensors (FBGS)). New types of communications paradigms (e.g., wireless, large bandwidth wired transmission) have emerged, resulting generally in very large sensor networks (up to several hundred sensors, if one moves towards the concept of “Smart Dust” (Boukerche *et al.* 2006, Agogino and Tumer 2006)) installed permanently on structures and able to record the vibrations in real-time and continuously.

On the software side, one major advance is the use of statistical methods (Worden *et al.* 2000, Basseville *et al.* 2000, Kullaa 2003) for more robust and reliable damage detection, even under changing environmental conditions (Sohn 2007). A second advance is the use of output-only measurements in order to extract dynamic features (stochastic subspace identification (Peeters and De Roeck 1999) or for damage detection (Basseville *et al.* 2000)). Localization and quantification of damage can also be performed using advanced machine learning techniques (such as neural networks (LeClerc *et al.* 2007)).

One might ask, what are the current problems in the general development of SHM systems and in transferring the technology to the civil engineering environment? The development of the S3HM

[1]The 4th International Conference on SHM for Intelligent Infrastructures was held at ETH Zurich in July 2009.

consortium involved a number of discussions of this issue; the researchers concluded that pressing problems were:

- The amount of data generated by large sensor networks is too large to be dealt with in an efficient manner.
- Feature extraction is not an automated process and requires qualified human interaction.
- The structures are subject to many sources of variability (temperature, humidity, traffic, ...) which may cause false alarms in the SHM system.
- Efficient damage localization can be performed through learning algorithms, but the data for training is missing.
- The damage scale is very small so that global approaches may not be sufficient to detect it.

The research objectives of the consortium were then formulated in terms of the following perceived needs:

1. efficient data reduction techniques;
2. efficient and automated feature extraction methods;
3. reliable methods to deal with environmental and operational variability;
4. efficient training of machine learning techniques, including the sourcing of appropriate training data (representing potentially diverse damage states);
5. a multi-scale approach in order to deal with very local damage. This includes the design and optimisation of appropriate sensor networks.

While this list is not necessarily exhaustive, few would argue that the issues there are not all major hurdles to the widespread use of SHM. Addressing the needs is the driver for the S3HM project, and some of the progress to date is described in the following sections. It is clearly not possible in a publication of this nature to explain the individual developments in any detail, so only the major salient points are given. Each of the following sections focusses on an individual partner in the S3HM project.

2. Data reduction in large sensor networks

The main task of the *Université Libre de Bruxelles* (ULB) within this project is the development of sensor networks and associated data reduction techniques. In order to deal with the very large amount of data coming from large sensor arrays, a technique based on modal filters has been proposed. Together, the developments attempt to address the first two identified needs of the introduction here, namely: efficient data reduction techniques and efficient and automated feature extraction methods. The modal filters can be seen as a single sensor built from a large network of sensors (Fig. 1(a)); the individual outputs are combined into a single output by means of a linear combiner. This single output can be designed such that it mimics the behavior of a single degree of freedom system, in which case the filter is called a “modal filter”. The filter can be tuned to any of the modes of the structure in the frequency band of interest. There is, in addition, the possibility of multiplexing by changing the linear combiner coefficients in real time, so that the same sensor array can be used for many modal filters.

One interesting feature of the modal filters is the fact that, if a global change is applied to the structure (i.e., a temperature variation), the shape of the output of the modal filter does not change as much as if a local stiffness variation is applied. Local stiffness changes are characterized by the occurrence of spurious peaks in the modal filters at the resonance frequencies of the structure (Fig. 1(b)). This effect has been studied in (Deraemaeker and Preumont 2006).

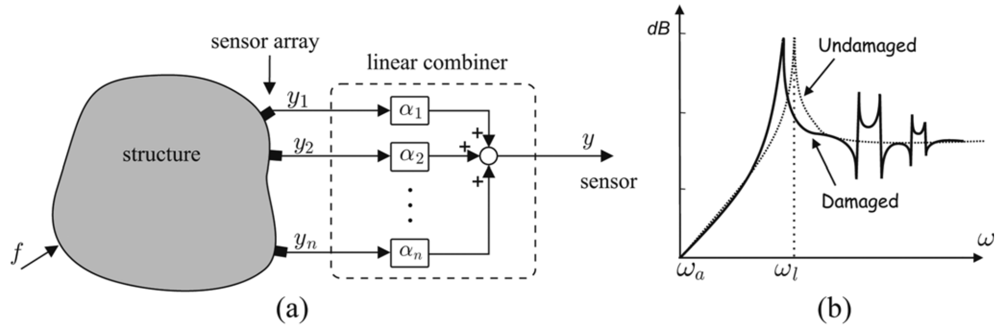


Fig. 1 (a) A large sensor array with a linear combiner to form a single output sensor and (b) modal filter output: undamaged and damaged structures

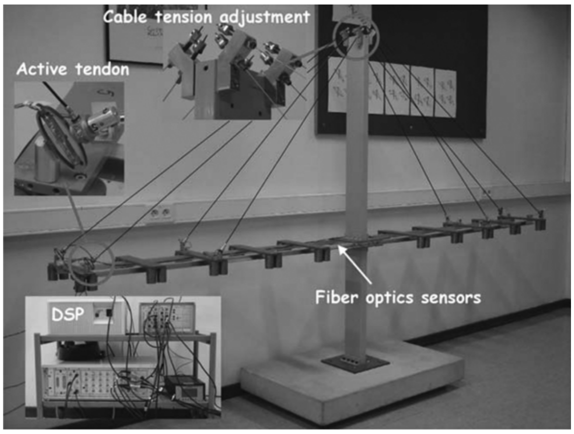


Fig. 2 Experimental small scale mock-up of a cable-stayed bridge

The rather high sensitivity of modal filters to local changes and low sensitivity to global changes makes it a good candidate feature in order to differentiate between damage and environmental effects, and this addresses need number 3 of the last section. Experimental work has also started in ULB. A small scale mock-up (Fig. 2) of an instrumented cable-stayed bridge has been built. It is equipped with accelerometers, force sensors and piezoelectric actuators. Further instrumentation is foreseen (piezoelectric patches, optical FBG sensors). This mock-up will be used for the validation of the different techniques developed in S3HM.

3. Automated output-only modal identification

The work of *KULeuven* is focused on feature extraction based on output-only vibration measurements and this addresses the second of the needs enumerated in the introduction - the efficient and automated extraction of damage sensitive features. In this framework, a novel procedure for the automation of Operational Modal Analysis (OMA) has been developed; such a procedure is highly desirable for the continuous monitoring of a structure's modal parameters (eigenfrequencies, damping ratios, and mode shapes). The procedure is based on the Reference-based Stochastic Subspace Identification (SSI/

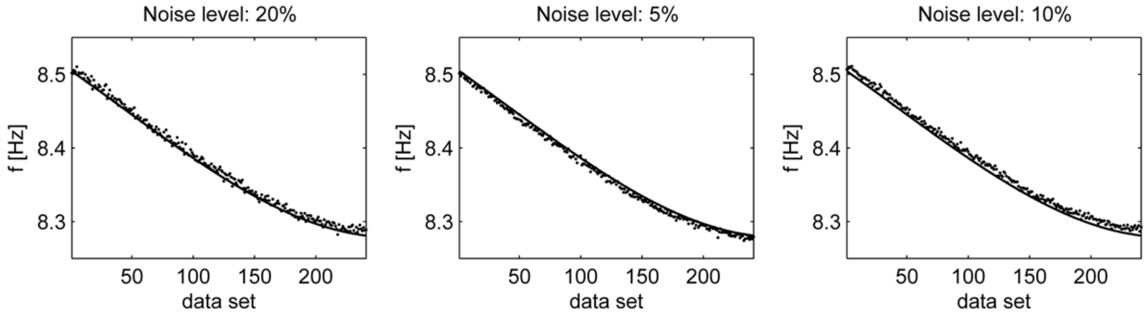


Fig. 3 True (solid line) versus automatically identified (dotted line) eigenfrequency

ref) method (Peeters and De Roeck 1999), which is known to be one of the most accurate output-only system identification methods for operational modal analysis.

The automation is based on a novel definition of a modal transfer norm, which is a measure of the contribution of a particular mode to the total response of the structure. It is described in more detail in (Deraemaeker *et al.* 2008). The automated operational modal analysis procedure has been successfully validated on 20 series of 241 simulated bridge data sets, where in each set, the modal parameters were allowed to change due to (simulated) environmental effects and damage of the bridge. (Fig. 3) shows some of the results from this study; in each case the graph shows a comparison between a true natural frequency and that identified by the automated modal analysis. The figures show that, even in the face of increasingly noisy environments (noise added to the vibration response data before identification), the algorithm is able to track the natural frequency extremely effectively.

4. Removal of environmental effects

The research at *Helsinki University of Technology* is focused on the elimination of environmental effects from the data using latent variable models and this addresses the third identified need of the introduction - a means of effectively dealing with operational and enviromental variations. The identification and correction of faulty sensors was also studied and, to some extent, this is aimed at addressing the need for robust and optimised sensor networks.

The well-known problem of environmental or operational influences on damage-sensitive features was approached utilizing latent variable methods, in which the measurement of the environmental variables is not necessary. Different linear and non-linear models have been studied, including factor analysis (FA), missing data analysis (MDA), mixture of factor analyzers (MFA), and non-linear factor analysis (NLFA). The linear methods proved to work best in practice due to their simplicity, robustness, speed, and possibilities for automation. The algorithms were studied with numerical and experimental data from a wooden bridge, the Z24 Bridge, and a vehicle crane (Kullaa 2002, Lamsa and Kullaa 2007, Kullaa and Heine 2007).

The test setup of the wooden bridge is shown in Fig. 4. Random excitation was applied to the structure using an electrodynamic shaker and the response was measured with fifteen accelerometers. Small point masses were added to represent damage. The features used for damage detection were the natural frequencies and modal co-ordinates identified using the stochastic subspace method (Peeters

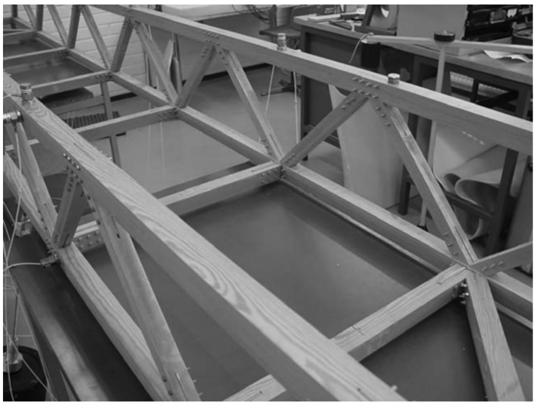


Fig. 4 Monitoring setup of the wooden bridge with a shaker, accelerometers, and added mass representing damage

2000). They were observed to be quite sensitive to temperature and humidity, making damage detection difficult.

To eliminate the environmental influences, MDA was applied to the feature vector. First, the training data were acquired to build the covariance model. Each feature **u** was then estimated in turn using the remaining variables **v**. The expected value of the feature **u** was computed by (Sorenson 1980)

$$\hat{\mathbf{u}} = \mu_u + \sum_{uv}\sum_{vv}^{-1}(\mathbf{v} - \mu_v) \tag{1}$$

where μ_u and μ_v are the mean values of **u** and **v**, respectively. $\sum_{uv}$ and $\sum_{vv}$ are the corresponding blocks of the partitioned covariance matrix $\sum$. The largest principal component of the residual, or the difference between the measured and estimated feature, was then used for damage detection. Fig. 5 shows the so-called control charts for damage detection of the wooden bridge. (The control chart simply shows a derived quantity which is known to stay within prescribed limits if the system or structure remains in normal condition.) The plotted statistic is the average of four consecutive variables. Any value outside the dotted lines (the control limits) indicates potential damage. It is clear that, without removal of the environmental effects, fault detection is not possible and false alarms are caused by environment changes alone; using the latent variable models however, damage detection capabilities

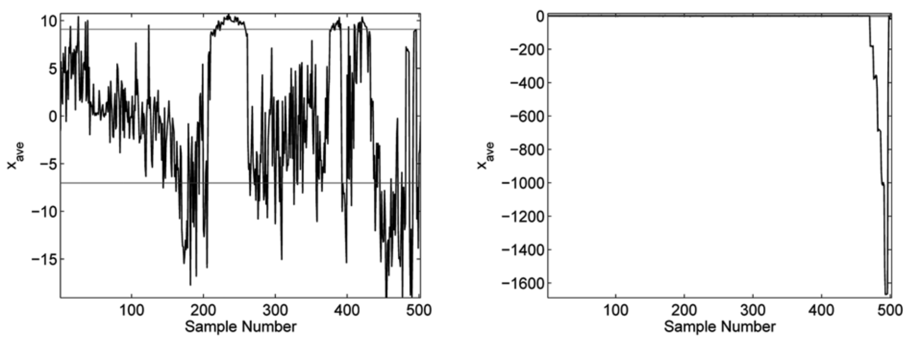


Fig. 5 Control chart for fault detection: (a) without removal of environmental effects and (b) with removal of environmental effects

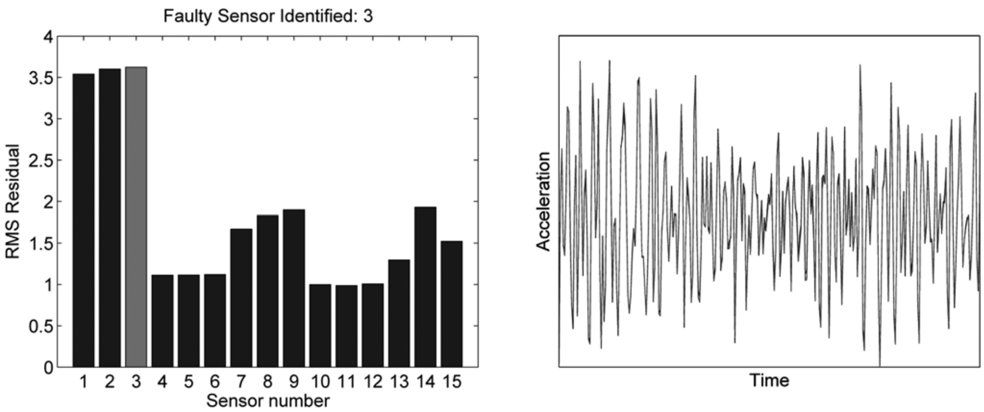


Fig. 6 (a) Faulty sensor identification (red bar) and (b) sensor correction (blue is true sensor and red is estimated sensor)

can be recovered.

A similar approach has been used to identify and reconstruct a faulty sensor reading using missing data analysis. In multichannel vibration measurements with enough redundancy, it is possible to estimate a sensor response using the others (Eq. (1)). The change in the error, or residual, between the true and estimated sensor is an indication of a fault. Once the faulty sensor has been identified, it can be substituted by the estimated sensor. As the sensor estimation uses time histories directly, without a feature extraction process, it is believed that a sensor fault can be distinguished from damage or environmental effects. Different types of sensor fault: bias, complete failure, drifting, and precision degradation, have been studied using both numerical and experimental vibration data and modifying one sensor to represent the faulty sensor. Sensor faults were investigated with the wooden bridge model experiments. The sensor fault was perfectly detected and the faulty sensor was correctly identified (Kullaa 2007). An example of faulty sensor identification and reconstruction, in which a bias fault was introduced into sensor 3, is shown in Fig. 6. The left figure shows the RMS residual between the measured and estimated sensor. The maximum value reveals the faulty sensor. A detail of estimated sensor 3 is plotted in Fig. 6 on the right. Superimposed is the corresponding true sensor without fault. It can be seen that the faulty sensor was correctly identified and its response reconstructed with high accuracy.

5. Training of machine learning techniques

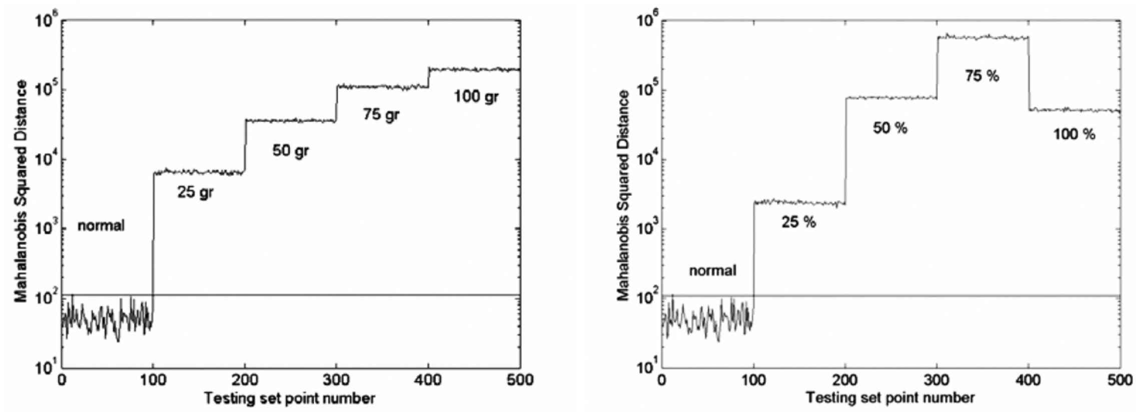
One of the fundamental problems in data-driven Structural Health Monitoring (SHM), and the focus of much of the *University of Sheffield's* work, is associated with sourcing data which is characteristic of the various damage conditions of interest. The research is thus intended to address the fourth need for SHM identified in the introduction - a means of sourcing data for machine learning methods which does not involve damaging a real structure.

Where the structure of interest is of high value, as is typically the case in the monitoring of civil and aerospace structures, it is inconceivable that data could be obtained by damaging the real structure. Among the alternatives available, is the possibility of generating data from an appropriate physics-based numerical model, e.g., a Finite Element (FE) model. One of the possible problems there, is

Fig. 7 Experimental Wingbox structure

that the required model fidelity may need to be so high, that model development and benchmarking/updating costs might themselves be prohibitive. In (Barthorpe *et al.* 2008) an approach for evaluating the impact of changes in model fidelity has been developed and used to investigate the impact of two fidelity factors on feature generation for an experimental structure. The study is based on a model aircraft wingbox component (Fig. 7), incorporating realistic features: ribs, stringers, rivets and bolts. The two fidelity factors investigated were the mesh density of one of the components, and the impact of FE updating. The results were encouraging in indicating that lower-fidelity models can still have value in selecting features for novelty detection.

Also based on the experimental wingbox, the objective of (Papatheou *et al.* 2009) was to investigate a means of experimentally generating pseudo-damage data which represents the features of the unknown true damage state with enough fidelity to allow the successful use of pattern recognition. The procedure does not, however, damage the real structure in any way. The pseudo-faults themselves are simply added masses at points on the structure. In this study, the object of the exercise was simply damage detection or novelty detection; the idea was to determine features appropriate to detect a 'crack' on one of the wingbox stringers without actually damaging the structure. As proxies for the damage, a number of small masses were added to the stringer. Features were then identified in



(a) (b)

Fig. 8 Outlier statistics: (a) mass added and (b) saw cut

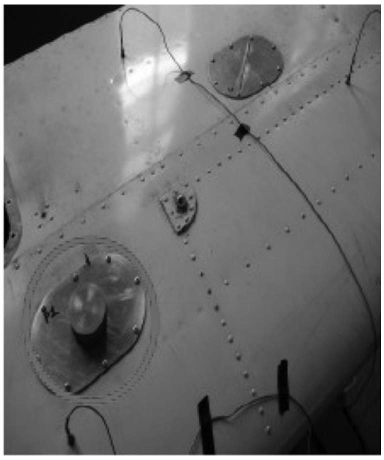


Fig. 9 Full-scale aircraft wing

the form of transmissibility functions (for responses measured at either end of the stringer). The features were refined by selecting small regions of frequency which showed sensitivity to the adding of the small masses. Once a number of candidate features had been identified, the relevant point of the stringer was damaged by the introduction of a saw cut and the features were assessed and ranked according to their ability to detect the real damage. Fig. 8 shows a novelty index defined in terms of the Mahalanobis-squared distance (Worden *et al.* 2000). In Fig. 8(a), the statistic is shown as a function of increasing added mass, and in 8(b) as a function of increasing cut depth. It is clear from this exercise that the idea of using 'pseudo-faults' shows promise for feature selection in the absence of true damage data.

In Papatheou *et al.* (2008), the pseudo-fault approach was demonstrated on a full-scale aircraft wing structure (Fig. 9), for a more difficult damage *localisation* problem. In this case, two inspection panels on the wing were identified and copies of each panel were made with a substantial saw cut in each. The localisation problem was posed in terms of finding which of the two panels had been replaced by a copy containing a cut. The approach depended critically on using the 'network of novelty indices' approach to damage identification developed in earlier studies (Manson *et al.* 2003). Features for a neural network classifier were selected as before, from transmissibility functions measured on the wing, by observing which features proved sensitive to small masses added to the panels. These features were then converted to outlier scalars as described in Manson *et al.* (2003) and these data were used to train the classifier. Once the classifier was established, it was tested on data measured from the cut panels.

The results of the study were extremely encouraging; it proved possible to design a classifier with zero misclassification rate on the true damage data using a neural network trained on only the pseudo-fault data.

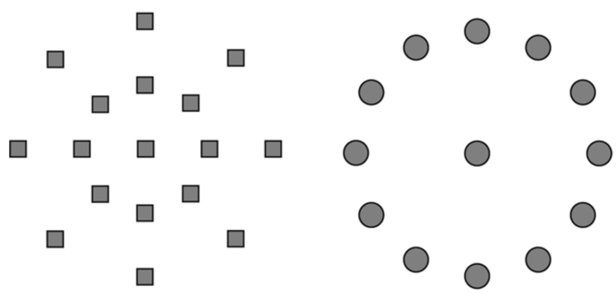
6. Local damage detection technique

A local damage detection technique has been developed by the *Institute of Fluid-Flow Machinery* (IFFM). It is based on Lamb wave propagation using the concept of phased arrays (Malinowski *et* *al.* 2007). This local method is complementary to the vibration-based methods and is capable of detecting much smaller defects than in case of vibration-based methods. The main problem is that Lamb wave propagation signals are very complicated and difficult to interpret. For this reason, special signal processing and damage visualization methods were investigated. The final result of signal processing is a map which indicates the location of damage.

First, numerical simulations were conducted on a square aluminium plate (1×1×0.001 m). The idea was to use actuators/sensors in a concentrated configuration located in the center of the plate. A study was performed in order to show which arrangement of the transducers gave the best damage localization capabilities. The work is an extension of the previous work performed in the field of linear phased arrays which consist of several transducers placed along a straight line. All of them may act as a wave sources and receivers or only some of them are actuators and the rest sensors. Registered signals are processed by a beam-forming algorithm. IFFM proposed a new approach to the linear phased array idea. Instead of using only one array, a configuration consisting of four arrays was introduced with a common middle transducer. Each array is rotated by 45 with respect to the previous one (star shape, Fig. 10(a)). Another configuration was studied which utilizes an advanced signal processing technique (Wandowski *et al.* 2007) which is different from the phased array concept and can be described as a form of elastic wave signal tomography. In the second (clock-like) configuration, a central transducer is surrounded by a circular array of transducers (Fig. 10(b)). Two strategies were considered: (i) only the central transducer is used as a wave transmitter while the remaining circular transducers work as sensors, and (ii) all combinations of actuator-sensor pairs are used. In the former case, the number of signals to be processed is much lower than in the latter case, so that signal processing is faster. The damage localization results are similar in both cases, but also using transducers on the circle as actuators appears to lead to improved (angular) damage localization; however, this only appears to be true for isotropic materials.

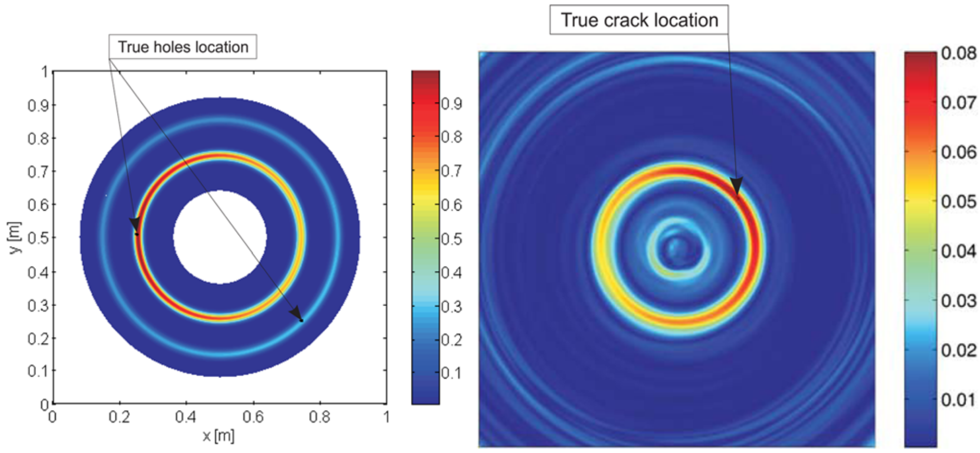
Comparing the results of the damage localization algorithms using star shape and clock-like configurations of transducers, it can be concluded that both methods give a similar inspection. Both methods can theoretically use damage-state signals only, but in practise, reference signals appear to be necessary in order to obtain satisfactory damage localization. The clock-like configuration guarantees almost the same accuracy of damage detection at each angle, while the star configuration suffers from false damage indications due to side lobe effects.

Experimental investigations were also carried in order to test the efficiency of the damage detection method. From the emitted and received signals, a damage map is obtained; such damage maps are presented in Fig. 11 for the star shape and clock-like configurations. The maps show that



(a) (b)

Fig. 10 (a) Star shape configuration and (b) clock-like configuration



(a) (b)

Fig. 11 Localization maps: (a) Two drilled holes (diameter 6 mm) - star shape configuration and (b) 1 mm crack - clock-like configuration

the true damage locations correspond to high values in the measured damage map. It can be observed that even very small cracks can be identified with very good accuracy (the difference between the maximum value of the damage map presented in Fig. 11(b) and the centre of the crack is about 6 mm).

7. Conclusions

This paper summarizes briefly the ideas and the work performed in the S3HM (Smart Sensing for Structural Health Monitoring) project. The main objective of the project is to take advantage of new advances in instrumentation, hardware, signal processing and data mining possibilities in order to explore new avenues in vibration-based SHM applications and address perceived needs for the effective transfer of the methodologies into the civil engineering domain (or indeed to large-scale high-value structures in general). Many potentially useful ideas have been developed within the project in pursuit of the design of robust vibration-based SHM systems for implementation on actual structures, and the paper gives the basic details of various advances emerging directly from S3HM. The paper hopefully illustrates the use of complementary skills of the various research groups involved and therefore makes a case for an interdisciplinary approach to SHM research. Different laboratory experiments have been set up throughout the course of the project and they will serve for further validation of the methods and concepts, with the hope of implementing an SHM system on a real structure in the near future.

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