Using genetic algorithms to optimize an active sensor network on a stiffened aerospace panel with 3D scanning laser vibrometry data

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Abstract. With the increasing complexity of aircraft structures and materials there is an essential need to continually monitor the structure for damage. This also drives the requirement for optimizing the location of sensors for damage detection to ensure full damage detection coverage of the structure whilst minimizing the number of sensors required, hence reducing costs, weight and data processing.

An experiment was carried out to investigate the optimal sensor locations of an active sensor network for detecting adhesive disbonds of a stiffened panel. A piezoelectric transducer was coupled to two different stiffened aluminium panels; one healthy and one with a 25.4mm long disbond. The transducer was positioned at five individual locations to assess the effectiveness of damage detection at different transmission locations. One excitation frequency of 100kHz was used for this study.

The panels were scanned with a 3D scanning laser vibrometer which represented a network of ‘ideal’ receiving transducers. The responses measured on the disbonded panel were cross-correlated with those measured on the healthy panel at a large number of potential sensor locations. This generated a cost surface which a genetic algorithm could interrogate in order to find the optimal sensor locations for a given size of sensor network. Probabilistic techniques were used to consider multiple disbond location scenarios, in order to optimise the sensor network for maximum probability of detection across a range of disbond locations.

1. Introduction

Acousto-ultrasonic induced Lamb waves are a long-established technique for detecting damage in structures. The principle involves exciting a piezoelectric transducer mounted to the structure’s surface which induces a Lamb wave that is then detected by another transducer mounted at a different location on the structure. If damage occurs within the field between the two sensors, the signal propagation is altered resulting in a quantifiable difference in the signal received.

Adhesively bonded metallic joints have been used in the primary structure of aircraft for the past fifty years [1]. Bonding as opposed to mechanically fastening stiffeners to the aircraft’s skin is advantageous as it can reduce the mass of the joints, distribute the stress loading more evenly and be
more resistant to environmental effects which an aircraft experiences [2]. Adhesive bonding is also less labour intensive and more cost effective than using mechanical fasteners [3].

Though adhesives have been used in the secondary structure without arrestment fasteners they are rarely used in the primary structure (i.e. the structure in which the occurrence of failure would be catastrophic). Without arrestment fasteners there is a lack of confidence in the reliability of the joint [4]. From the experience of the Royal Australian Air Force (RAAF) 53% of defects detected on aircraft structures such as the F-111 were found to be bond failures [5]. Many cases of adhesive bond failure have been found to be the result of improper application of the adhesive or insufficient surface preparation [4] i.e. human error in the manufacture of the joint.

Though it has been proven that bonded joints are more resistant to fatigue loading as well as being able to withstand higher peak loading [5], the degradation of the adhesive layer over time is not fully understood [6]. This uncertainty in the condition of the bond throughout the aircraft’s in-service life requires monitoring through non-destructive techniques to ensure airworthiness. If a sensor network could be installed to monitor damage and degradation of the bonded joint an “as required” inspection program could be utilised. However sensor networks need a high probability of detection whilst minimizing the weight penalty they add to the overall structure. Hence, understanding the optimal location of sensors for this monitoring is of the utmost importance.

2. Experimental Setup

Two stiffened panels of dimensions 1250mm x 1250mm were constructed from 3mm thick 6082-T6 aluminium plate. An unequal angle stiffener made from 6082-T6 aluminium was bonded to each plate using commercially available Araldite® 420 structural adhesive. The film thickness of the adhesive was regulated using 0.1mm copper wire gauges to achieve the optimum shear strength [7].

On one of the panels an intentional disbond was induced at the centre of the stiffener of 25.4mm in length which covered the width of the stiffener. This was induced by installing PTFE tape over this region of the bond which was then removed once the adhesive had cured.

A square region of 625mm x 625mm in the centre of each panel, on the face with the stiffener was designated the area of investigation in an attempt to reduce reflections from the edges of the panels.

Five excitation sites were designated along the left hand boundary of the investigation area. By having multiple excitation sites the effectiveness of the transducer-disbond path could be investigated, in effect simulating different disbond positions relative to a single transducer site.

Vibrometer measurement points were set up within the investigation region. No measurement points were positioned within a 25mm wide region on either side of the stiffener. This was due to the positioning of the laser heads which resulted in the stiffener casting a ‘shadow’ where it was impossible for all three lasers to align.

There also were no measurement points positioned in a 78mm wide region to the right of the excitation sites in order to save acquisition time as preliminary tests had demonstrated insignificant findings in this region. The dimensions of the panel are shown in Figure 1.

A PANCOM Pico-Z transducer was excited with a 10-cycle sine burst generated by Physical Acoustics WaveGen function generator software connected to Physical Acoustics μdisp/NB-8 hardware. The peak-to-peak amplitude of the excitation signal was 160 V. An excitation frequency of 100kHz was selected for this experiment. A 10 V peak-to-peak wave was also generated and used as a reference signal for triggering the acquisition of the vibrometer. A repetitive trigger rate of 20 Hz was used as this gave sufficient time for the induced wave energy to fully dissipate before taking the next measurement. Velocity amplitudes were investigated at 825 points with two hundred measurements being recorded at each point. These measurements were then averaged in order to improve the signal to noise ratios.

The vibrometer used for this experiment was the Polytec PSV-500-3D-M. This vibrometer uses three laser heads to measure each scan point. The measurements recorded by each laser head can then be used to calculate, using trigonometry, both the in-plane and out-of-plane modes. Due to taking measurements from three heads it is less important for the laser heads to be perpendicular to the
structure under test with a 3D scanning system when compared to a 1D system. The investigation region was coated with retro reflective glass spheres which improves the signal quality by increasing the amount of back scattered light. During testing each panel was laid on ‘bubble wrap’ packaging material to acoustically uncouple it from the floor. A series of markers were laid within the laboratory and on the panels to ensure that each panel was positioned in the same place relative to the laser heads. A low pass front end filter was applied to the measurements with the filter frequency set 20kHz above the excitation frequency to filter out high frequency noise.

Figure 1: Dimensions of the Stiffened panel, excitations sites and scan area

3. Optimisation problem
The number of possible sensor network combinations increases with the number of sensors by a multiple of the respective binomial coefficient. In this experimental study, the number of possible sensor locations is 825.

It is massively computationally expensive to evaluate the effectiveness of every possible solution as the number of sensors in the network increases, ruling out simple optimisation techniques such as an exhaustive search. A list of the maximum number of sensor combinations is shown in Table 1 for networks of up to 5 sensors.

Table 1: The number of sensor network combinations for a given number of sensors in the network

| Number of Sensors in network, \( N_s \) | Number of possible sensor network combinations |
|----------------------------------------|-----------------------------------------------|
| 1                                      | 825                                           |
| 2                                      | 339900                                        |
| 3                                      | 93245900                                      |
| 4                                      | \( 1.92 \times 10^{10} \)                     |
| 5                                      | \( 3.15 \times 10^{12} \)                     |

3.1. Genetic Algorithms
Genetic Algorithms (GAs) are an optimisation technique developed by Holland [8] that are based on the theory of evolution to find the optimal solution. Each ‘generation’ produces more suitable solutions and less suitable solutions are discarded in a manner analogous to Darwinian evolution.
Genetic algorithms have advantages over other optimisation techniques as they have the ability to ‘mutate’, allowing the algorithm to interrogate the whole solution space to find the global minimum or maximum rather than converging on local minima or maxima. The way that algorithm interrogates a relatively low proportion of the total solution space is also not as computationally expensive as other techniques[9]. Figure 2 shows the schematic representation of a GA [10]. A brief overview of a genetic algorithm is given here. For further explanation the reader is referred to Haupt and Haupt [9].

There have been many studies conducted that have used genetic algorithms to optimise sensor networks for many active and passive sensing problems [11-13]. One of the biggest issues however, as with any optimisation problem, is defining the cost or fitness function for the GA to interrogate.

3.2. Time Window

The data sets (healthy and delaminated) were first correlated for the entire sample length of the measurements (1.6ms). This however produced very low cross-correlation coefficient values due to the reflections and refraction patterns caused by the disbond resulting in significant differences in the edge reflections.

To improve the correlation between the two data sets, a 200μs time window containing only the incoming wave was used for the cross-correlation. The time window was decided by taking the maximum velocity value in the first 700μs of the entire sample length for the healthy data set. A 40% threshold value was then calculated and the arrival of the wave was determined when the threshold was first crossed. A pre-trigger of 14% was also applied to ensure that the wave front was captured.

3.3. Cross Correlation

The cross-correlation technique has been proven to be a sufficient means of identifying the presence of damage in an acousto-ultrasonic (AU) system [14] where waves received are correlated with each other to identify any differences. Typically a value of unity for the cross-correlation coefficient indicates that the received waves are identical. A value less than unity identifies that the waves are different and hence typically the presence of damage.

By calculating the cross-correlation coefficient for each measurement pair it is possible to produce five data sets with an assigned cross-correlation coefficient for each point. These five data sets serve as a fitness for sensor locations for each excitation site. The aim of having numerous excitation sites was to produce results that were representative of having the disbond in different locations relative to the excitation site. A plot of the cross-correlation data set for excitation site 3 is shown in Figure 3. For this study, only the out-of-plane wave modes have been considered.

The low correlation behind the disbond observed in Figure 3 is the result of a refraction pattern produced by the Lamb wave’s interaction with the disbond. This is also observed on the excitation side of the stiffener as diagonal refraction fringes produce areas of low cross correlation values. This identifies the presence of disbond.
3.4. Cross-Correlation Error

In this study there was a degree of error observed in the cross-correlation coefficient as only values below unity were observed. The cause of this was the fact that two separate stiffened panels were used giving rise to errors due to slight manufacturing differences, minor alignment errors between panels and, most likely, due to inconsistencies in the acoustic coupling of the excitation transducers on each panel.

To quantify the cross-correlation error, a time window of 80ms from the arrival of the wave at nearest measurement to each excitation site was taken so as to minimise any reflection effects. Samples of 5 x 5 measurement points nearest to excitation site were cross-correlated for each excitation study and the cross-correlation coefficients were averaged. Over the five sets of data the average cross-correlation coefficient was calculated to be 0.91 giving a 9% error.

3.5. Cost Function

In order to determine the optimal sensor locations for a sensor network that would detect the disbond regardless of excitation site, a statistical measure was needed in order to determine the fitness of the location across the five data sets – i.e. how well would the proposed sensor network allow the detection of damage for any of the five potential excitation locations?

Each sensor location had five cross-correlation coefficients (one for each excitation site). For each sensor network, the lowest cross-correlation coefficient was selected for each excitation site data set. These values were then used for the cost calculation as demonstrated for a two sensor network in Table 2.

| Excitation Sites | 1     | 2     | 3     | 4     | 5     |
|------------------|-------|-------|-------|-------|-------|
| Sensor A         | 0.8087| 0.6007| 0.7355| 0.6502| 0.8791|
| Sensor B         | **0.6412**| 0.9576| **0.6435**| 0.8222| **0.5681**|
| Best Cross-Correlation Coefficient | 0.6412| 0.6007| 0.6435| 0.6502| 0.5681|

The cost was calculated by adding the standard deviation, $\sigma$, and the square root of the mean squared error of the five cross-correlation values as shown in Equation (1). The objecting of the GA was then to seek the minimum cost for a given sensor network.

$$cost = \sigma + \sqrt{\frac{1}{5} \sum_{i=1}^{5} x_i^2}$$

*(Equation 1)*

Where $\sigma$ is the standard deviation, $n$ is the number of datasets and $x$ is the cross – correlation coefficient.
If sensors in the network were found to be redundant (i.e. none of their cross-correlation coefficients were selected for calculating the cost) then a cost penalty was assigned to that sensor network. A schematic for calculating the cost is outlined in Figure 4.

![Schematic of the process for calculating the cost](image)

**Figure 4:** Schematic of the process for calculating the cost

4. Results

4.1. Genetic Algorithm performance

Binary encoding was used by the genetic algorithm in this experimental study. Each potential sensor location (i.e. locations 1-825) was described by a binary string (known as a ‘gene’). The number of sensors in the network defined how many genes made up the full binary string (known as a ‘chromosome’). Each chromosome described one candidate sensor network within the population of solutions. These chromosomes were used by the algorithm to mate and mutate.

As the total number of measurement points was 825, which requires a 10 digit binary string to resolve, artificially high cross-correlation penalties were assigned to binary values representing locations greater than 825 hence giving solutions containing these genes poor fitness. The initial population used was $40 \times$ the number sensors in the network, $N_s$. The size of the initial population was increased as the size of the search space increased as to ensure sufficient sampling of the search space.

The selection method used for mating the chromosomes was a simple pairing technique where the best two solutions in the population are selected for mating, then the next best two until the whole mating pool has been paired up. A randomly assigned cross-over point was used for each mating pair. This gave the algorithm a good ability to carry forward the best attributes of the solution without continuously producing poor solutions which can be a drawback of fixed point cross-over schemes.

An allele mutation allowed the algorithm to explore more of the search space and hence prevented the algorithm from seeking local minima by continually exploring new regions of the solution space. A probability of mutation of 0.1 was used for this problem. The fittest 10% of solutions were made immune from allele mutation. This prevented good solutions being mutated into poorer solutions, and hence being discarded.

As with all genetic algorithms, convergence can prove to be an issue as it is not always clear that the optimal solution has been reached. This is a drawback of GAs as every possible solution is not exhaustively considered. In this study, a solution was deemed to be optimal when the minimum cost had not been improved upon for 2000 generations. This approach has previously be found to be successful by Clarke [10]. The performance of the GA is displayed in Figure 5.

4.2. Sensor locations

Having run the GA for different sizes of sensor network it is possible to make a direct comparison of the performance of the proposed solutions as shown in Figure 6.
The proposed solutions show a 22% reduction in cost as the number of sensors in the network increases from one to two sensors. Improved sensitivity can be achieved as more sensors are added to the network with the cost reducing by 50% with a five sensor network. The best network solution entirely depends on the requirements and constraints of the network. However these results suggest that a three sensor solution offers an acceptable compromise between performance and mass / expense penalty.

Figure 5: Convergence of the minimum cost for different values of $N_s$

Figure 6: Calculated costs for each number of sensors in a sensor network

GAs are renowned for producing ‘less-intuitive’ solutions to problems. The locations of the sensors produced by the GA are shown in Figure 7. Some of the sensor locations are reused in more than one sensor network demonstrating that many of their cross-correlation coefficients are low.

Figure 7: Optimal sensor locations for number of sensors, $N_s$, for five disbond locations

5. Discussion and Conclusions
The results presented demonstrate a methodology for optimising sensor locations with the use of scanning laser vibrometry. The ability to autonomously collect data from several potential locations dramatically decreases experimental time allowing a more thorough study to be conducted.

The locations that have been selected by the algorithm at first may not seem entirely intuitive such as selected location on the upper right on of the stiffener in the three sensor network. This particular location detected low correlation for one disbond location with the other sensor in the network detecting low correlation for the other disbond locations.

The work presented here is part of a more extensive study in which the effects of different excitation frequencies will be investigated together with the influence of in-plane wave modes on sensor locations.

Conclusions that can drawn be from this work are:
Sensor location for active structural health monitoring is a complex problem and the positioning of the sensors is important in order to achieve the greatest likelihood of detecting the damage.

Laser vibrometry is a powerful tool in producing data for a vast number of potential sensor locations.

Genetic algorithms offer many advantages in producing solutions that offer acceptable fitness.

Though optimisation studies are of great importance, it is up to the sensor network designer to ultimately set the objective of what the network is trying to achieve. Hence, it is the responsibility of the designer to assess the best solution, using optimisation techniques such as this as a decision making aid rather than blindly relying on computational optimisation techniques.

This study only considers centrally located disbonds. The study could be expanded to investigate disbonds at stiffener edges.

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