Identification of Key Performance Indicators for SHM in Structures of Increasing Complexity Based on Artificial Neural Networks

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Abstract
Lamb wave based technology being one of the advanced approaches in the field of ultrasonics, is being widely considered to perform Structural Health Monitoring (SHM) in damage tolerant aeronautical structures. Damage tolerance is a concept in which damage up to a tolerable size is allowed to exist in structural components before those components will have to be repaired. To get such damages detected reliably, an automated inspection process based on SHM technology is considerable. However, it is important to know at what features such SHM technology needs to look at such that the appropriate key performance indicators (KPI) can be well identified. Such an identification may be best done through numerical simulation which is the purpose of the paper being proposed here. Referring to guided ultrasonic waves and here specifically to Lamb waves different modes being sensitive to the tolerable damages defined have to be identified such as the S0 mode for through thickness cracks and possibly others for further types of damage. To optimize the quality of the Lamb wave modes generated in the first place, two actuators have been placed opposite to each other on the top and the bottom of the plate like structure considered. Changes in the plate geometry such as thickness have been detected through a mode conversion and the dispersive effect of the mode considered i.e. the S0 mode. In this paper the approach on how to determine the input features for an artificial neural network (ANN) will be described on a numerical basis as well as the resulting KPIs obtained through the ANN. At first, the SHM of a damage tolerant structure is explained for a fuselage like structure in which cracks emanate from the rivet holes and where the SHM technique to be applied will be based on Lamb waves.

1. Introduction

1.1. Damage tolerance design
Aircraft today are mainly designed on the basis of the damage tolerance principle. A damage tolerant design is considered when a damage can be tolerated that will not lead to catastrophic failure and hence compromise safety until repairs can be performed. Due to fatigue, cracks can emanate from defined locations and their size is allowed to grow to the tolerable size before can lead to failure of the structure. This critical point can also be called the damage tolerance limit. It is specifically defined through the residual strength capacity that degrades with the level of stress applied where the failure of structure occurs when the residual strength is less than the normal service load due to the accumulating damage. Figure 1 shows the behavior of crack size with respect to the life and the residual strength of a typical aluminium 2024 structure.

![Figure 1: Relationship between crack size and number of cycles (a) and residual strength (b) [Quora.com]](http://www.ndt.net/?id=25048)

1.2. Metallic patched repair
When a structure gets damaged it needs to be repaired. With damage tolerant structures this incident when a damage has been detected and has not become critical, hence it is still in the tolerable range. In case of a metallic aircraft fuselage structure, the damage is repaired using a metallic patch. In the regions where the aerodynamic smoothness is important, a flush type repair is performed. Usually in a flush type repair the damaged area is removed using a circular or rectangular cut in the skin. The cut is then filled with the same material and the thickness of the skin. The doubler is placed on the bottom of the skin and has twice the thickness of the skin [1]. The filler and the doubler are fastened to the skin by using rivets. Figure 2 shows a typical assembly of the flush type metallic patch repair.
1.3. Need for SHM

As an aircraft is subjected to a variety of loads, cyclic stresses and due effects of aging, there are chances that the structure develops cracks in the areas of high stress concentrations. For example, in the fuselage skin, the stress is high in the area around the rivet holes and there is a high probability that cracks can develop. Figure 3 shows a widespread fatigue crack in a lap splice of a fuselage. If the crack is identified in an earlier stage, there will be a necessity for the structure to be monitored such as by a SHM system that has to reliably detect when the damage tolerant limit of the structure is to be achieved.

When the damage has been repaired with the metallic patch, there may be a chance that a crack may develop from the new rivet holes in the skin of the aircraft or on the doubler. Hence, there is a requirement for the SHM system installed to monitor the structure on a regular basis.

1.4. Principle

An ultrasonic guided (Lamb) wave based SHM system is capable of detecting cracks of which the lengths can be principally to be considered in the mm range and above. This can be demonstrated by using numerical simulation. A crack length of 100 mm may be a realistic figure to be considered as a critical (damage tolerance) limit of the structure considered. Guided waves are usually sent as a package (group) through a structure, where the group defined through phase and group velocity disperses and hence generates a complexity where signal analysis may be necessary. This is underlined by the fact that there are two types of modes (symmetric and antisymmetric) where in the current case a predominant first symmetric S0 mode of excitation is considered only for the study in order to reduce complexity. This is obtained by actuating the actuators shown in Figure 4 simultaneously out-of-phase.

1.5. Model specification

The two following models will be considered to explain the concept:
- Fuselage plate specimen - Model 1
- Patched repair specimen - Model 2

The structural material is considered to be aluminium 2024 plate with properties \( \rho = 2700 \text{ kg/m}^3, \nu = 0.33 \) and \( E = 70 \text{ GPa} \) and dimensions of 400x300x2 mm. All rivet holes have a diameter of 7.4 mm and are 25 mm equally spaced apart from each other as shown in Figure 5. For reasons of simplicity the rivets are considered as holes in the first place but will be considered as solid material in the future.

The actuator is 8 mm in diameter and 0.48 mm in thickness. The actuator material is considered to be Lead Zirconate Titanate (PZT-5A). For the model 1, a 1 mm wide through thickness crack is considered as shown in Figure 6. The crack emanates from the center hole and grows up to a length of \( 2a=100 \text{ mm} \). The center of the crack is located at \( (x, y) = 205,150 \text{ mm} \).

Assuming that the crack has reached the damage tolerance limit for Model 1, the structure is modified to a patch repair like specimen (Model 2). Model 2 is considered according to the Aviation Maintenance Technician Handbook [1]. A rectangular portion around the damage is removed. The corners are filleted with a radius of 5mm and this empty region is filled with a filler material of the thickness of 2mm to create a flush patch. To reinforce the filler material, a doubler of 4 mm thickness is used on the bottom of the skin as shown in Figure 5.
While Model 1 represents the pristine structure due to a crack and hence to repair, Model 2 represents the repaired structure where cracks are considered to develop in the skin and neither in the filler nor the doubler because the strength in the skin will be considered relatively low due to aging. Hence for Model 2, a crack is considered only on the skin starting from the new rivet holes. The center of the crack is located at (x, y) = 250,150 mm as shown in Figure 7, where doubler and skin are colored with blue and green for better visualization.

Figure 5: Top and front view of Model 1 - Fuselage plate with rivet holes (top). Model 2 - Repair patch with rivet holes (bottom). The red boxes represent the actuators and the green dots the sensor node arrangement respectively.

Figure 6: Model 1. A region near the damage, crack length = 30 mm (a) and zoomed in view of the crack (b).

2. Theoretical Background

Lamb waves are guided waves and are also called as plate waves because they occur in structures with a prismatic geometry (such as a plate) where thickness is constant and the difference in acoustic impedance to the neighboring environment is significant. Lamb waves are usually considered to have a wavelength in the dimension of the plate thickness and be dispersive. Depending on the frequency, the Lamb waves exhibit different orders of modes. At lower excitation frequencies, the zero-order modes S0 for symmetric mode and A0 for anti-symmetric mode occur only. However, when the excitation frequency increases, higher order modes start to occur in the propagating media as well, being named S1, S2, S3… for symmetric modes and A1, A2, A3… for anti-symmetric modes respectively. The propagating mode depends on the excitation frequency and the stiffness of the material and this relation can be summarized in the form of phase and group velocity dispersion diagram as shown in Figure 8 and Figure 9 respectively. For more intuition regarding the derivation of dispersion relation of Lamb waves, the reader is referred to [2].

Figure 7: Model 2. Region near damage, crack length = 30 mm (a) and zoomed in view of the crack (b).

Figure 8: Phase velocity dispersion diagram for Aluminium 2024 for 2mm thickness.
The frequency dispersion in the medium can occur when there is a change in geometry for example due to corrosion, damage or can occur due to the change in material properties for example due to the reduction of material stiffness, or aging of the medium the wave is propagating in. However, in this study, the analysis is performed based on the fact that the guided wave problem is defined for the dispersion due to the change in the geometry resulting from a crack.

3. Methodology

3.1. Finite element model

In order to generate the guided wave data, the finite element software COMSOL multi-physics has been used. The piezoelectric effect was achieved in COMSOL by using a multi-physics module called “Piezoelectric effect” which combines the physics of solid mechanics and electrostatics.

The two models - Model 1 and Model 2 with their respective material properties have been mentioned before. A total of 22 simulations were performed. They are:

- Model 1 pristine condition (1 simulation)
- Model 1 with crack of lengths 10 mm to 100 mm with step of 10 mm (10 simulations)
- Model 2 pristine condition (1 simulation)
- Model 2 with crack of lengths 10 mm to 100 mm with step of 10 mm (10 simulations)

The tetrahedral shape element with a mesh size of 3mm for the plate and 0.48mm for the transducers with a second order quadratic serendipity type discretization as shown in Figure 10 was used for both models. This study is performed based on the S0 mode which is sensitive to through thickness cracking. The mesh size was used according to a previous mesh study performed [3] for a 2 mm thick aluminium 2024 plate. A time step of 0.1µs was chosen according to the Courant-Friedrichs-Lewy Condition [4]. In order to study the effect of mode conversion, i.e. the effect of the A0 mode etc., a finer mesh size and time step is required. For each simulation, 150 µs of signal is recorded from each sensor node.

![Figure 9: Group velocity dispersion diagram for Aluminium 2024 for 2mm thickness.](image)

The excitation signal used for all the simulations was a 5-cycle Hanning window signal as shown in the Figure 11. Finally, the low reflecting boundary condition was defined for the four sides of the 400x300 mm plate for both Model 1 and 2 in order to dampen the effect of reflected waves. For the described configuration, each simulation consumed around 90 minutes for the solution.

![Figure 10: A second order tetrahedral element](image)

![Figure 11: A 5-cycle Hanning window excitation signal](image)

3.2. Sensor configuration

The physical geometry of the top and bottom actuator are placed at (x, y, z) = 80, 150, 2 mm and 80, 150, 0 mm respectively. The generated guided waves are measured using an array of sensors from node points. The arrangement is shown in the Figure 5 for both of the models in green dots and coordinates of the arrangement are as follows:

**Top** (Z = 2mm)
- X = 294 mm, Y= 90 to 210 mm with step of 10 mm.
- X = 318 mm, Y= 90 to 210 mm with step of 10 mm.

**Bottom** (Z = 0mm)
- X = 294 mm, Y= 90 to 210 mm with step of 10 mm.
- X = 318 mm, Y= 90 to 210 mm with step of 10 mm.

This configuration is the same for Model 1 and Model 2. From all the sensor node points the in-plane (x) and out-of-plane (z) displacements are recorded. In this study, the analysis will be demonstrated with “z” displacement. The “x” displacement will be used for a future study.
3.3. Signal processing and feature extraction

In view of damage tolerant design being established in aviation, it is assumed that the damage is known with regard to location and size. The parameter to be monitored is the varying length of the damage. A few signal processing techniques were performed on the recorded signals and a library of features were created.

A signal can be represented or viewed in different ways. The three representations of the observed phenomenon that were considered for the study are shown in Figure 12 and are the following:

- Recorded signal in time domain.
- Hilbert envelope of the recorded signal [3].
- Fast Fourier Transform (FFT) of the recorded signal.

In machine learning, a feature is an indicator and a measurable property which should possess information of the phenomenon being observed. Different features may indicate the current state of the phenomenon to be monitored with different accuracies. To form a library, a variety of features from the three representations mentioned above were collected by using the following five statistical techniques to form a library:

- Mean value
- Mean of the difference (Pristine signal - damage signal)
- Root Mean Square Deviation [3] between the pristine and the damage signal
- Linear correlation coefficient [3] between the pristine and the damage signal
- Mean absolute error [3] of the signal difference between pristine and damaged condition.

The data from the five statistical techniques are due to result in a single value each and these techniques were performed on all three representations which makes 15 features. Apart from these 15 features, three additional features were considered which are:

- Mean value after the difference of the FFT amplitudes (mean (FFT(pristine) - FFT(damage))
- Maximum value of the Hilbert envelope of the signal.
- Maximum value of the difference of the signal.

Hence for each signal, a library of 18 features was created programmatically using MATLAB. For example, if the signal for the pristine condition is \( X_1 \) and the signal for the damaged condition is \( X_2 \), the order of the 18 features are as shown in the Table 1:

<table>
<thead>
<tr>
<th>Feature number</th>
<th>Feature</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Mean of envelope of ( X_1 )</td>
</tr>
<tr>
<td>2</td>
<td>Mean of envelope of ( (X_1 - X_2) )</td>
</tr>
<tr>
<td>3</td>
<td>RMSD of envelope of ( X_1 )</td>
</tr>
<tr>
<td>4</td>
<td>LCC of envelope of ( X_1 )</td>
</tr>
<tr>
<td>5</td>
<td>MAE of envelope of ( X_1 )</td>
</tr>
<tr>
<td>6</td>
<td>Maximum of envelope of ( X_1 )</td>
</tr>
<tr>
<td>7</td>
<td>Mean of FFT of ( X_1 )</td>
</tr>
<tr>
<td>8</td>
<td>Mean of FFT of ( (X_1 - X_2) )</td>
</tr>
<tr>
<td>9</td>
<td>Mean of (FFT(( X_1 )) - FFT(( X_2 )))</td>
</tr>
<tr>
<td>10</td>
<td>RMSD of FFT of ( X_1 )</td>
</tr>
<tr>
<td>11</td>
<td>LCC of FFT of ( X_1 )</td>
</tr>
<tr>
<td>12</td>
<td>MAE of FFT of ( X_1 )</td>
</tr>
<tr>
<td>13</td>
<td>Mean of raw signal of ( X_1 )</td>
</tr>
<tr>
<td>14</td>
<td>Mean of ( (X_1 - X_2) ) of raw signal</td>
</tr>
<tr>
<td>15</td>
<td>RMSD of raw signal of ( X_1 )</td>
</tr>
<tr>
<td>16</td>
<td>LCC of raw signal of ( X_1 )</td>
</tr>
<tr>
<td>17</td>
<td>MAE of raw signal of ( X_1 )</td>
</tr>
<tr>
<td>18</td>
<td>Maximum of ( (X_1 - X_2) ) of raw signal</td>
</tr>
</tbody>
</table>

3.4. Artificial Neural Networks (ANN)

ANNs can be used for a variety of purposes in various fields in science where the common tasks include classification and regression analysis. The idea is to help the user to choose the best feature and best position to place a sensor and to predict the crack length reliably by using an ANN.

Before designing an ANN, one of the features was analyzed in order to get a clearer idea on how to choose the appropriate ANN architecture. For example, the amplitude of feature 8 from Model 1 at sensor node \( (x, y) = 318, 200 \) mm on the top surface is shown in the Figure 13. The figure is plotted with the mean amplitude from feature 8 with respect to the crack lengths which is represented in black dots. This plot reveals the non-linearity in data because the input is not proportional to the output. But even though there
is no continuous growth in the amplitude, an overall trend is observed that when the crack length increases, the amplitude of feature 8 increases as well. The crack length can therefore be represented as a function of the amplitude of the feature, which itself has been determined through the ANN.

A basic fully connected feedforward ANN with 2 neurons and 1 hidden layer was created. The hidden layer was configured with a tan-sigmoid function and the output layer was configured with a linear function as shown in Figure 14(a). The neural network was set to train each feature separately for each sensor for all crack lengths. For each sensor therefore, a total of 18 neural networks was created which results in the function with a relationship of 11 feature amplitudes (training dataset) to the crack lengths between 0 and 100 mm with a step of 10 mm (training targets).

The ANN was trained using a scaled conjugate gradient backpropagation training function which adjusts the weights and biases of the layers creating a relationship (the fit function in Figure 14(b)) between the feature amplitudes to the crack length. The network was trained with 100 epochs (iterations). If the network was therefore provided with a new value of the feature 8 from a crack length that it has not been trained with, the trained ANN will be able to interpolate and should predict the crack length.

In the example provided in Figure 14 an error of ±20 mm was observed. This error will differ for different features and for different sensor positions. For the specific example with feature 8 the training error can be reduced if the ANN was trained with neurons greater than 2 or with more hidden layers. However, the observed fit function was a complex overfitted function which is regarded as badly trained for the defined problem. An example of the overfitted function is shown in Figure 15 with the same data that has been used in the example from Figure 14 and also with same number of layers, same ANN parameters but by only changing the number of neurons from 2 to 20. This new ANN is good when considering training data because the error is reduced from ±20 mm of crack length to ±5 mm. However, clearly it does not form a continuous and good relationship between the feature amplitude and the crack length which will result in very bad errors for new values that will be tested.

ANN with 2 neurons was therefore created for the library of features for all individual sensors and for both of the models. To test the performance of the ANN, new simulations with 5 different crack lengths were carried out for each of the models. For model 1 crack lengths of 23, 35, 64, 76, 87 mm and for Model 2 crack lengths of 15, 34, 68, 73, 84 mm were considered for which the results are presented below.

4. Results and discussion

To compare the results, a map of accumulated sum of all features for the sensor node array Y = 90 to 210 shown in Figure 5 for each X position is plotted. The results are explained only for the sensor nodes on the top surface for each model because the bottom results are observed to be almost similar.
4.1. Layout of KPI map

A KPI map is the representation of all features for specific sensor arrays. The user can easily identify the KPI (or the best performance indicator or a feature) for the best sensor position. The layout of the KPI map is shown in Figure 16. Region 2 is the KPI map which represents the accumulated absolute error for the tested crack lengths. Region 4 represents the color scale for the map. Region 1 represents the mean error along rows for each sensor. Region 3 represents the mean error for columns which are the features.

The steps to calculate the accumulated absolute error for model 1 for the sensor array at X = 318 and for feature 8 as shown in the Figure 13 is given below:

- After the ANN has been trained with the amplitudes of feature 8, the function as shown in Figure 17 obtained.
- When the ANN is provided with new amplitudes of feature 8 from testing crack 0, 23, 35, 64, 76, 87 mm as described before, the ANN predicts the new crack lengths as 0, 36, 22, 75, 74, 91 mm. The value 0 represents the pristine condition.
- The absolute errors of these values are 0, 13, 13, 11, 2, 4 mm.
- The sum of absolute error values is 43. The value 43 is indicated in the KPI map in Figure 17.

4.2. KPI maps and interpretation

When interpreting the KPI map, the best performing features can be identified by the boxes which have the darker color as shown in Figure 17 and 18 respectively. The darker the color the less the error with the prediction of the new crack lengths is.

From the KPI map for both of the models, the sensor paths 120, 130, 170 and 180 showed on average lower error for many features when compared to other sensor positions as can be observed from region 1. The features like 2, 8, 15, 16, 17 and 18 showed very good performance in predicting the crack lengths.

In both of the models, the dark spots were seen relatively higher in a sensor array at X = 318 mm than in X = 294 mm. This effect can be explained by the wave propagation analysis through simulation. When observing the wave field, such an effect was caused due to the new waves being created due to wave diffraction when the waves
from the actuator strikes the crack edges. The wave fronts created from the edges of the crack causes interference and these interferences become stronger and more pronounced the farther the wave propagates. When the distance becomes longer, the stronger the information of the crack can be observed as shown in Figure 19. That is why there is less error for almost all the performance indicators at X= 318 mm when compared to X = 294 mm.

In both of the models, the reason why the sensors at location 90 and 210 have almost close to mean error of nearly 100 and above in region-1 is obvious because of the disturbances due to the holes. The reason why sensor locations in 140, 150 and 160 showed high error can be due to the presence of the crack itself but a future study with different crack locations needs to be made to study and verify this effect. Also, this effect can be the result of the interference phenomenon as explained before.

Feature 18 is the differential energy and the dark spots in the sensor locations 120, 130, 170 and 180 mm can be verified using the differential imaging from the wave propagation obtained from simulation and shown in Figure 20. From this figure Model 1 shows the differential image [5] between the pristine condition and a crack length of 80 mm which shows a high correlation to the sensor location 120, 130, 170 and 180 mm in the image and the feature 18 in KPI map. The same kind of relation between the differential image of Model 2 from Figure 21 and the KPI map of Model 2 can be observed. The sensor location 160 mm (close to the center in Y direction) shows high accuracy for feature 18 because the mode converted waves from the patch repair seems to have created this effect.
4.3. KPI and sensor location selection

In case the assumed models are to be used for real structures, the best sensor position and the KPI can be reliably determined by using the KPI map approach. Figure 22 shows the crack length determined by using the sensor node at \((x, y) = 318, 120 \text{ mm}\) with KPI (feature) 15, which is the RMSD value of the signals between the pristine and the damaged condition. This configuration is suggested because with only one sensor, it will be possible to reliably detect the crack length with good accuracy.

Likewise, the node position at \((x, y) = 318, 120 \text{ mm}\) can be also used for both models because of the dark spots in the KPI map which correlates to the high differential hotspot in the wave field.

5. Conclusion

From what has been said above, the following can be concluded:

- Numerical simulation is a good means for an enhanced understanding of guided wave behavior in damage tolerant structures even in the case of an enhanced structural complexity.
- Guided wave time domain signals being recorded can be analyzed with regard to a variety of techniques and statistical approaches from which a library of features can be extracted, which can also be considered as performance indicators in general.
- By feeding an ANN with features a function can be derived between the features and phenomena to be observed/monitored on the structure such as tolerable damages.
- The function determined between the features and the phenomena allows KPIs to be determined, which will provide the information on which of sensors’ signals one would have to concentrate most such that an optimum output of an SHM system is obtained.
- Accuracies of the KPI related predictions are in an acceptable range and still show hope and potential for further improvement.

6. References