Damage Detection using Matching Pursuit and Artificial Neural Network

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Abstract

In the area of Structural Health Monitoring (SHM) much attention has been paid to model based approach. Recently, the focus has shifted to data-driven techniques as it can even work with complex structures. This paper focuses on data-driven approach for SHM and highlights the application of Matching Pursuit (MP) and Artificial Neural Network (ANN) for damage detection using guided flexural waves in a one-dimensional beam. MP is used to decompose a signal into linear combination of waveforms, selected from a redundant dictionary. By selecting optimum number of iterations for MP, sparsity of the dataset is achieved and additionally the signal is de-noised. In this study finite element is used to simulate flexural wave response for thin aluminium beams with and without damage. Simulations are carried out at different frequencies for different kinds of damage. A prototype of the system is finally proposed to automatically provide user with near-real-time information about the structure’s condition.

Keywords: Matching Pursuit, Artificial Neural Network, Flexural wave, Damage Detection

1. Introduction

In recent times, there has been an increasing awareness of the importance of damage diagnosis systems in mechanical, aerospace and civil structures. It is required that a damage diagnosis system would appraise the user about the structure’s health, inform about any nascent damage in real time and provide a reasonable estimate of the remaining useful life of the structure.

To address the challenges in real time automatic damage detection two different approaches are used, model based and data driven based (or model-free). In the former, a precise mathematical model of the structure must be developed in advance, usually with an assumption that system under study is linear and time-invariant. This approach is based on known structural parameters. On the other hand data driven based approach does not require a prior knowledge of structure’s parameters, instead it directly relates the sensor data to locations of damage patterns. As this does not rely on an accurate mathematical model so it is more flexible and suitable for real-time damage detection.

Guided flexural waves have been widely used for nondestructive damage testing of various structures like rods, plates, pipes etc. The method employs mechanical stress waves that propagate along an elongated structure while guided by its boundaries. Compared to standard ultrasonic technology, guided-wave inspection technology can cover a wider range by propagating elastic pulses along waveguides and capturing the reflected pulses from the damage. However, reflected wave from a crack may be significantly distorted as elastic waves are usually dispersive [1], making the damage testing a challenging task.

The objective is to develop an efficient signal processing technique effective for guided wave signals and to devise an automatic damage detection technique which can be used for online health monitoring using a minimum possible processing power. In the existing literature, MP has been mainly developed for signal compression[2]. It is currently being used for video size compression [3] and ECG signal compression [4]. Uses like image classification using MP have also been illustrated in the literature[5]. In the field of NDT, its use for signal processing of guided waves is being explored [6]. Attempts have been made to overcome challenges due to multiple modes and dispersion in guided waves for reliable damage detection [7][8]. But, not much research has been done to explore the
possibility of using MP along with machine learning algorithms [9] for structural health monitoring. Hence, in this study we try to automate the damage detection process using ANN.

The technique proposed in the study is based on MP and reduces the number of data points by more than 40% which is essential for machine learning algorithms as they are inefficient with large datasets. However, it leads to loss of some important features of the signal. To address this challenge MP is deployed in two stages. It is initially used to make the signal sparse while retaining the most relevant features which is then passed for ANN pattern recognition. Using ANN, approximate location of the damage is estimated. Further, to increase the accuracy of the technique, part of the original signal in vicinity of the estimated location is extracted and MP is used again on that small part of the signal. Here, MP is used to de-noise the extracted signal, retaining almost all major features of the signal, which is then analyzed to improve the estimation of location of the damage. Hence, by using MP in two stages along with ANN, a good accuracy for damage detection is achieved.

2. Simulation of Guided Wave Response

A one-dimensional beam of length 50 cm and width 1 cm is used for the simulations. To incorporate damage in the beam, a rectangular notch of dimension 1cm x 0.1cm is considered as shown in Fig 1. Database generation for the analysis is done using FE simulations in ANSYS. PLANE182, a four node element is selected as the element type to model the structure. For material properties data for aluminium is taken. Density is set to 2712 kg/m$^3$, Poisson’s ratio to 0.3 and Young’s modulus taken for the isotropic beam is 70 GPa. Element edge length is set to as 1mm and total number of elements are around 5000. One of the edges of the rod is clamped and a 3.5 cycle sinusoidal modulated tone burst is used for the excitation signal as shown in Fig 2. The signal is given as a force to give transverse disturbance in the beam and velocity response is then recorded. White Gaussian noise is added to velocity data and signal to noise (SNR) ratio is kept at 130. The created database has more than 1500 data-points and has noisy guided wave response. So, by using simulations the database for signal processing is created.

![Figure 1: Schematic of the notched beam](image)

![Figure 2: Excitation signal (sinusoidal modulated tone burst)](image)

3. Proposed Technique

3.1 Guided wave velocity calculation

Guided flexural waves deform the structure transversely as they propagate. Transverse waves are dispersive as different frequencies travel at different speeds. The phase speed is given by Eq.1 [10].

$$C_B = \left( \frac{E I \omega^2}{\rho A} \right)^{\frac{1}{4}}$$

(1)

where, $E$ is Young’s modulus, $I$ is area moment, $A$ is the area of cross section, $\omega$ is angular frequency of excitation, $\rho$ is the density of the beam.
3.2 Increasing sparsity using MP

The matching pursuit algorithm iteratively projects a signal $f$ onto a given over-complete dictionary $D$ and chooses functions from dictionary called atoms $g_t$ that best matches the signal in each iteration, shown in Eq.2. Hence, the algorithm allows a highly adaptive representation of the signal. The dictionary is designed such that it represents well the characteristics of a given signal.

$$f(t) = \sum_{n=0}^{\infty} a_n g_{\gamma_n}(t)$$  \hspace{1cm} (2)

where, $n$ indexes the atoms that have been chosen and $a_n$ a weighting factor for each atom.

The algorithm for matching pursuit[2]:

**Input:** Signal $f(t)$, Dictionary $D$

**Output:** List of Coefficients $(a_n, g_{\gamma_n})$

**Initialization:**

- $R_1 \leftarrow f(t)$
- $n \leftarrow 1$

**Repeat**

- find $g_{\gamma_n} \in D$ with maximum inner product $|\langle R_n, g_{\gamma_n} \rangle|$
- $a_n \leftarrow \langle R_n, g_{\gamma_n} \rangle$
- $R_{n+1} \leftarrow R_n - a_n g_{\gamma_n}$
- $n \leftarrow n + 1$

**Until stop condition**

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**Figure 3:** Matching Pursuit dictionary used for analysis

The objective for signal processing using MP is to increase the sparsity (compression) of the dataset as well as to de-noise the signal. Although compression of signal is essential for machine learning algorithms, it leads to loss of important features from the response which is unfavorable. Hence, MP is deployed in two stages. For both stages, symlet wavelet packet presented in Fig.4, is used as the dictionary which is modified version of Daubechies wavelets with increased symmetry.

Next step of proposed technique involves using MP to reduce the number of data-points i.e. increasing the sparsity of the dataset as shown in Fig 4. This is achieved by tuning the stopping criteria for MP (number of iterations). When the number of iterations is very large, the resultant dataset after applying MP is almost similar to the original dataset. However, if the number of iterations is less then important features are lost and the retained energy is not sufficient for estimation of the damage. Hence, an important step for this technique is to tune the stopping criteria so that only a minimum number of required data-points are extracted.
ANN training is implemented using MATLAB Neural network Toolbox. The entire waveform data after using MP is used as the input vector. The input is hence, a collection of numbers indicating velocity which make up the time-domain response waveform. The size of dataset after applying MP is around 600 data-points as compared to more than 1500 data-points initially. The target data is provided in the form of binary number indicating the presence of damage. For reflection from a damage it is set to 1 and 0 for rest of the data-points.

A two-layer feed-forward network space [11], with sigmoid hidden and output neurons, can classify vectors arbitrarily well, given enough neurons in the hidden layer. The network is trained with scaled conjugate gradient back-propagation[12]. For the analysis 10 hidden layers have been considered as shown in Fig 5. Training is done using velocity data without noise and with damage at three different locations (7, 9 and 11 cm). Output of this network is a probability measure of the damage, i.e. 1 for points with damage and 0 for points which are classified as non-damage points. For noisy input the probability is in the range of 0.8-1 for damage location data-points.

After using ANN on the velocity dataset, we get a probability data for all the data-points in the dataset. Using that, the damage location can be estimated as velocity of the wave and the time for the reflection from the damage is known. However, this estimate is not accurate as increasing sparsity of the dataset leads to loss of some features of the dataset. Therefore, the velocity data is extracted again from the original database for the time where the probability of the damage is more than 0.8. This way, only the reflected wave is extracted.

As the original database has noise, MP is used again for noise reduction using the same dictionary, shown in Fig 6. This time the number of iterations for stopping criteria is restricted to almost 15% of the iterations used in the first level of MP because the echo from the reflection is a small part of the database. A de-noised reflection is obtained which is used to ascertain the accurate location of the damage.
3.5 Damage location estimation

The last step of the technique involves analyzing the de-noised reflection response. From the extracted dataset the maximum velocity is computed. Starting point for the reflection is considered around 10% of the maximum value. Thus, the time for the starting point of the reflection is obtained. Using the velocity calculated from Eq. 1 and the time obtained, distance of the damage is obtained.

4. Results

Analysis has been performed for two frequencies of excitation, 175 kHz and 200 kHz. Damage notches have been taken at 6 different locations for the study. Neural network is trained for damages at 7, 9 and 11 cm. The first stage of matching pursuit leads to quick estimation of the approximate location of the damage presented in Fig 4. Using the proposed two stage MP with ANN as shown in Fig 7 error of less than 1.5 cm is obtained which is shown in Fig 8.
5. Conclusions

A two-stage matching pursuit approach was proposed to estimate the location of damage from transverse wave signals measured in beams. The key idea in this study is to make the technique computationally efficient so that online health monitoring can be performed using the limited processing power available on-board. The proposed method successfully extracted meaningful pulses from simulated noisy signals. Very small echoes reflected from a crack, which would be difficult to detect by other methods, were captured by the approach. The errors in predicted damage location were less than 3%, hence, the technique possess potential for SHM of real-life aerospace structures, which would be explored in the future work. Future scope also lies in implementation of other efficient machine learning techniques.

6. References


