Proposed Health State Awareness of Helicopter Blades using an Artificial Neural Network Strategy

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ABSTRACT

Structural health prognostics and diagnosis strategies can be classified as either model or signal-based. Artificial neural network strategies are popular signal-based techniques. This paper proposes the use of helicopter blades in order to study the sensitivity of an artificial neural network to structural fatigue. The experimental setup consists of a scale aluminum helicopter blade exposed to transverse vibratory excitation at the hub using single axis electrodynamic shaker. The intent of this study is to optimize an algorithm for processing high-dimensional data while retaining important information content in an effort to select input features and weights, as well as health parameters, for training a neural network. Data from accelerometers and piezoelectric transducers is collected from a known system designated as healthy. Structural damage will be introduced to different blades, which they will be designated as unhealthy. A variety of different tests will be performed to track the evolution and severity of the damage. A number of damage detection and diagnosis strategies will be implemented. A preliminary experiment was performed on aluminum cantilever beams providing a simpler model for implementation and proof of concept. Future work will look at utilizing the detection information as part of a hierarchical control system in order to mitigate structural damage and fatigue. The proposed approach may eliminate massive data storage on board of an aircraft through retaining relevant information only. The control system can then employ the relevant information to intelligently reconfigure adaptive maneuvers to avoid harmful regimes, thus, extending the life of the aircraft.

Keywords: Structural health, helicopter blade, neural network

1. INTRODUCTION

Importance of Early Fault Detection

There has been considerable progress in the area of fault detection and isolation resulting in several possible approaches [1, 2, 3, 4]. In the case of helicopter blades, early fault detection is vital in the prevention of catastrophic and possibly fatal mechanical failures. Amura et al. carried out an investigation of a military helicopter crash that resulted in the fatality of the entire crew [5]. While four main rotor blades were found close to the impact point, a fifth blade was found approximately 900 m away from the wreck leading Amura et al. to conclude that the cause of the crash had been the failure of this blade. The rotor blade consists of a long hollow 6061-T6 aluminum extrusion. Visual examination of the fracture surface of the aluminum extrusion indicated fatigue crack growth followed by ductile overload separation. Examination by optical and electronic microscopy of the fatigue fracture revealed an abnormal incision that appeared to be the fracture origin site. Further examination through electronic microscopy with X-EDS analyzer showed evidence the crack origin was the result of an in appropriate tool used to remove pockets during maintenance activities [5]. In this instance, a neural network strategy may have proven useful as part of an NDT (non-destructive testing) regimen for early fault detection. While neural networks can be used simply as a fault detection device the ultimate goal is to devise a robust fault tolerant system as part of a hierarchical control scheme.

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Neural Network Strategy

In general, there are two methods of approaching the analytical fault detection problem: the model-based approach and the signal-based approach. In the model-based approach, the engineer has access to an analytical or knowledge based model of the system whose behavior is being monitored. These models usually consist of linear systems which are more easily characterized. The data based approach bypasses the step of obtaining a mathematical model and deals directly with the data. This method has greater viability due to the non-linearity of a helicopter blade rotor system. One particular application of a neural network is monitoring a specimen in order to detect major changes in the operating system. In this case, the neural network is trained on a well-behaving system in order to detect anomalies in the output of the system being monitored. This paper proposes implements training a neural network on a system with known faults in parallel with a healthy system known as supervised learning. This method presents a challenge, however, in that it requires a representative sample of all faults in a training set in order to work properly [6]. Helicopter blades have a wide spectrum of faults with varying degrees of severity. Thus, adequate training may prove resource and time intensive.

Neural networks are typically implemented in applications such as automatic vehicle control [7], pattern recognition [8, 9] function approximation, and robotics applications [10]. As described in [11, 12], a multi-layer feed-forward network consists mainly of sensory units that constitute the input layer, one or more hidden layers and an output layer.

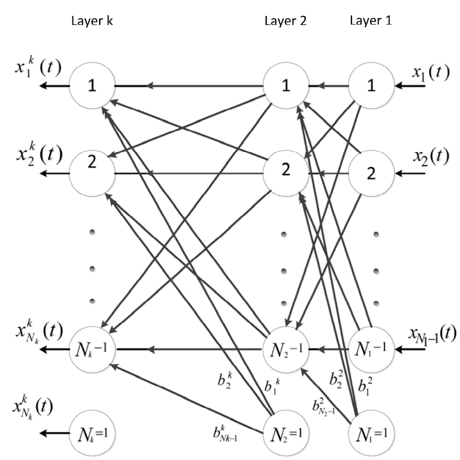

Figure 1. Schematic of feed-forward multilayer perceptron network [13].

As shown in Figure 1 and described in [11, 12], each node is connected to all nodes in the adjacent layer by links (weights), and computes a weighted sum of the inputs. An offset (bias) is added to the resultant sum followed by a nonlinear activation function application. The input signal propagates through the network in a forward direction on a layer-by-layer basis. Consequently, the network represents a static mapping between inputs and outputs.

As per [11, 12], let k denote the total number of layers, including the input and output layers. Node(n,i) denotes the i^{th} node in the n^{th} layer, and $N_n - 1$ is the total number of nodes in the n^{th} layer. As shown in Fig. 2, the operation of node$(n+1,i)$ is described by the following equation [13]:

$$x_i^{n+1}(t) = \varphi\left(\sum_{j=1}^{N_n-1} w_{i,j}^n \, x_j^n(t) + b_i^{n+1}\right) \tag{1}$$

where, $x_i^n(t)$ denotes the output of $node(n,j)$ for the t training pattern, $w_{i,j}^n$ denotes the link weight from node(n,j) to the node$(n+1,i)$. b_i^n is the node offset (bias) for node(n,i) [13].

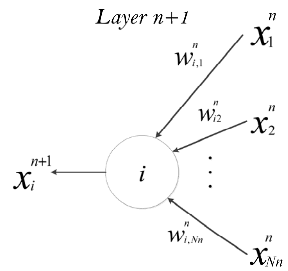

Figure 2. Node $(n+1, i)$ representation [13].

The function $\varphi(.)$ is a nonlinear sigmoid activation function defined by [13]:

$$\varphi(w) = \frac{1}{1+e^{-aw}} \qquad a > 0 \text{ and } -\infty < w < \infty \tag{2}$$

For simplicity, the node bias is considered as a link weight by setting the last input N_n to $node(n+1, i)$ to the value of one as follows [13]:

$$x_{N_n}^{n}(t) = 1, \qquad 1 \leq n \leq k$$

$$w_{i,N_n}^{n} = b_i^{n+1}, \qquad 1 \leq n \leq k-1$$

Consequently, (1) can be rewritten in the following form [13]:

$$x_i^{n+1}(t) = \varphi\left(\sum_{j=1}^{N_n} w_{i,j}^{n}\, x_j^{n}(t)\right) \tag{3}$$

In general, raw data should not be directly applied to the input layer of a neural network. If the given data is high dimensional, it will increase the number of weights in the neural network and slow down the training algorithm. Pre-processing the data in order to obtain important features, thus reducing the dimensionality of the training data and the number or required weights. A basic algorithm for applying neural networks to fault detection consists of using a signal processing technique to obtain a figure of merit f for the different time signals. If f is highly dimensional, a feature extraction algorithm to reduce its dimensionality with keeping most of its information content transforming f into f_e. Finally, the neural network is trained on f_e in either supervised or unsupervised mode. The following sections will discuss the figures of merits used and the accompanying pre-processing technique [6].

2. VIBRATIONAL DATA

Damage Precursors

Non-destructive damage evaluation techniques are important for maintaining high-value mechanical systems such as a helicopter rotor. Fault detection usually consists of three levels of characterization: recognition that damage has occurred, location of the fault, and severity of the fault. Cyclic operational loading and processing flaws may induce localized compliance and micro cracks which can propagate into macro-scale cracks. While conventional methods for damage prediction of high value mechanical systems uses strain measurement and crack detection schemes, these approaches are not typically capable of detecting precursors to damage. Cole and Habtour used a slender steel 1095 cantilever beam which was subjected to nonlinear vibratory-based excitation in order to initiate damage precursors [14]. As the beam accumulated cyclic fatigue damage, the resonance frequency was decreased while the beam tip displacement increased [14]. In this case, the beam tip displacement was a more prominent feature and provides a promising parameter for neural network training.

Damage precursor classification is vital in the representative sample of the fault spectrum. Ideally, the training set will include the complete spectrum from a healthy system to a failed system with a high resolution of intermediary phases in order to diagnose fault severity.

Fault Location

Fault location in cantilever beam may be assessed by treating the beam as two separate beams connected by a torsional spring at the fault location [15, 16]. It is experimentally verified that the structural effect of a cracked section can be represented by an equivalent spring loaded hinge. Das and Parhi propose a nondestructive evaluation procedure for identifying crack location in a structure using modal test data [16]. Using the first three natural frequencies through vibrational measurements, curves of crack equivalent stiffness versus crack location are plotted. The intersection of the three curves are then used to study crack location and size. A simply supported analytic beam model shows that absolute changes in the curvature mode shapes are localized in the region of damage [16]. Thus, curvature of the mode shapes is a promising parameter for a neural network.

3. PROPOSED EXPERIMENTAL SETUP

The experimental setup consists of a scale aluminum helicopter blade exposed to transverse vibratory excitation at the hub using single axis electrodynamic shaker as shown in Figure 3a. The data acquisition will feature a number of hardware redundancies including accelerometers, piezo electric transducers, strain gauges, and fiber optics in order to improve the efficacy of the neural network training and accuracy of the outputs. The training phase will consist of using known healthy systems in parallel with a wide range of faulty systems from damage precursors to catastrophic failure. Over the course of the study, different data processing algorithms and input features/classifiers (such as natural frequencies, modal shapes, etc.) will be used to train the neural network until satisfactory fault characterization is achieved as shown in Figure 3b. Accurate fault classification is important as it will eventually be used in a hierarchical control system to apply the correct counter measures to mitigate further damage and fatigue.

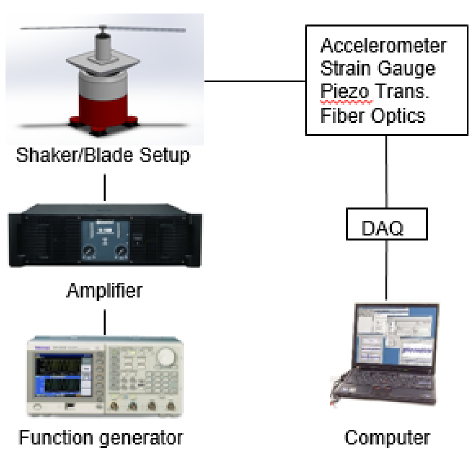

Figure 3. a) Experimental setup.

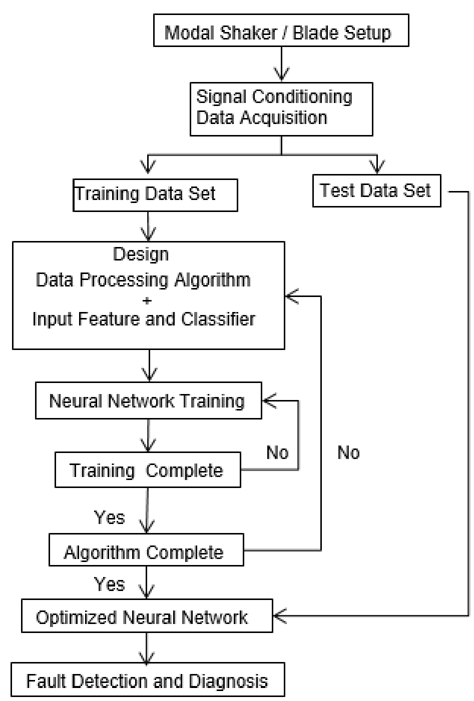

Figure 3. b) Neural network training flowchart.

4. PRELIMINARY STUDY

Methods

A preliminary study was performed on a 12" x 1" x 1/16" 6061-T6 aluminum cantilever beam with large relative faults in order to examine neural network strategies. The faults consisted of a 1½" diameter hole located 2" from the fixed end and a ½" transverse crack located 2" from the fixed end. The beam was ended was deflected by ½" and released. The resulting vibrational data was acquired using a ADXL335 accelerometer located at the free end of the cantilever beam and atmega328 microcontroller. Vibrational data was collected from 20 healthy, cracked, and hole specimens in a vibration isolated environment and a non-isolated environment. The natural frequency, settling time, and damping ratio of each data set was collected. Figure 4 shows a sample of the data collected.

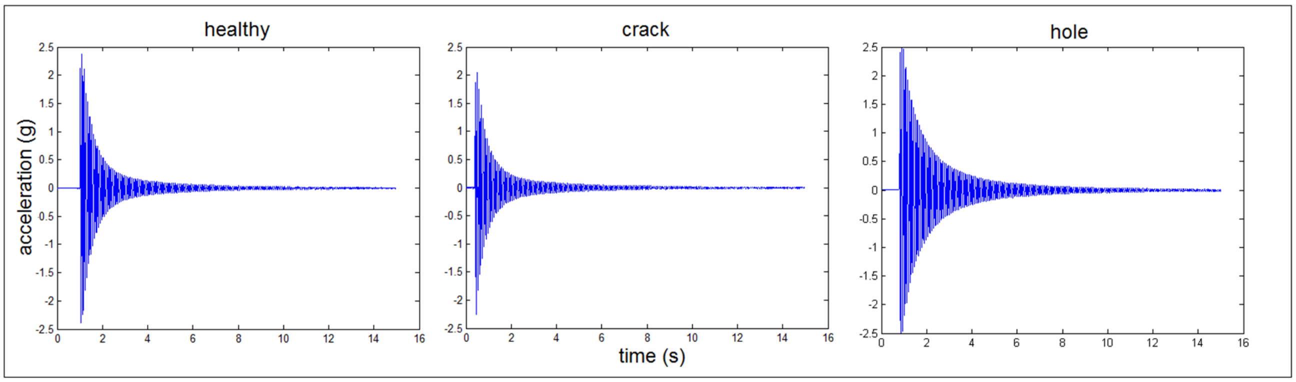

Figure 4. Vibrational data collected at a sample rate of 1 kHz at for healthy and faulty specimens.

Data Pre-Processing

Raw vibrational data consists acceleration and time data approximately 15 seconds long at a rate of 1 kHz. Feeding this data directly into the neural network input would cause tremendous strain on the training phase. Thus, relevant characteristics such as natural frequency, settling time, and damping ratio were extracted from the data. The log decrement method was used to calculate the damping ratio where $x(t)$ is the amplitude at time t, T is the period, and n is the number of peaks away from $x(t)$.

$$\delta = \frac{1}{n} ln \frac{x(t)}{x(t+nT)} \tag{4}$$

$$\xi = \frac{1}{\sqrt{1+\left(\frac{2\pi}{\delta}\right)^2}} \tag{5}$$

The natural frequency and second order approximation of the system were modeled using equations (6) and (7), respectively.

$$\omega_n = \frac{\omega_d}{\sqrt{1-\xi^2}} \tag{6}$$

$$\frac{Y(s)}{U(s)} = \frac{{\omega_n}^2}{s^2 + 2\xi\omega_n + \ {\omega_n}^2} \tag{7}$$

The normal distribution of these parameters was created in order to assess the viability of a neural network for fault detection using these properties as shown in Figure 5.

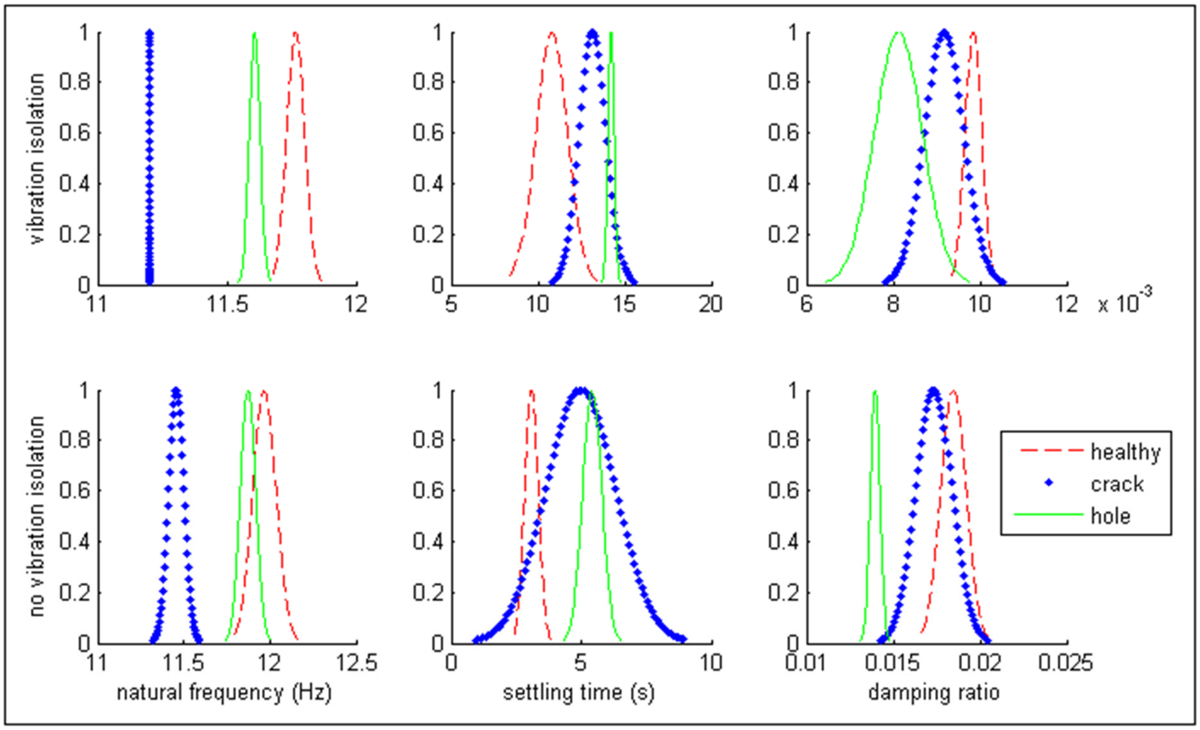

Figure 5. Normal distribution of different parameters for healthy and faulty specimens.

Figure 5 shows the highest differentiability between the natural frequency of each specimen. While settling time and damping ratio show significant overlap in their distributions, there is still a consistent trend allowing for added redundancy.

Neural Network Training

The normal distributions were used to simulate 6,000 pairs of healthy and faulty samples. A supervised learning method was used to train the neural network with these samples in which the healthy and faulty samples were known. The output target classification of the known samples consisted of a 1x3 binary logic matrix in which a healthy sample was denoted by [1 0 0], a cracked sample was denoted by [0 1 0], and a sample with a hole was denoted by [0 0 1]. Figure 6 shows the basic neural network structure in with three inputs (natural frequency, settling time, and damping ratio) and an output classifying the system as being healthy, having a transverse crack, or having a hole. In order to test the neural network, an unknown sample was used and the neural network was tasked with correctly classify the health state.

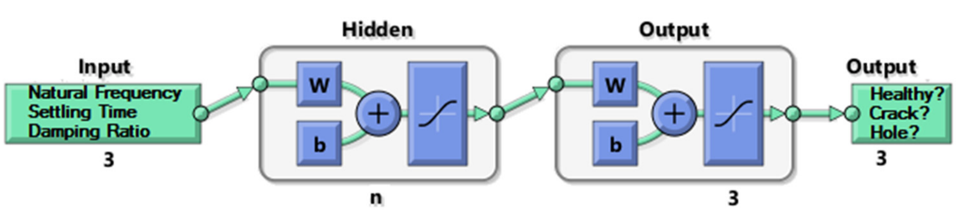

Figure 6. Basic structure of the neural network.

Results of the Preliminary Study

The number of hidden layers was varied until the neural network was able to correctly identify all test samples. Figure 7 shows the confusion matrices for each hidden layer.

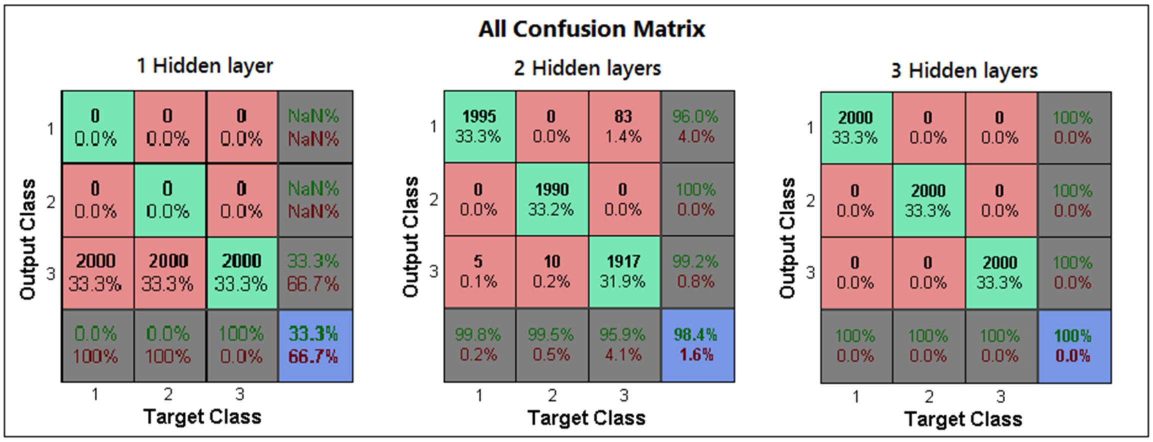

Figure 7. Confusion matrices for three types of hidden layers.

Choosing the correct number of hidden layers is vital in optimizing limited computing resources. The results show that one hidden layer is insufficient for identifying the health state of the specimens. However, with two hidden layers, the neural network achieved an overall 98.4% success rate in correctly identify the health state of the aluminum cantilever beam. At three hidden layers, the neural network was able to identify the health state with 100 percent accuracy. Figure 8 shows that the neural network achieved the best validation performance at epoch 60 through batch training. Even by the 30th epoch, the MSE was below 0.001.

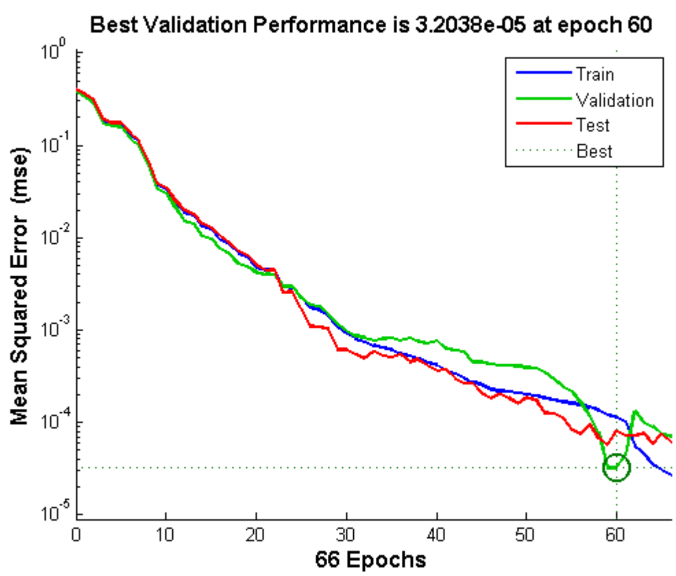

Figure 8. Validation performance at three hidden layers through minimization of the validation MSE.

5. CONCLUSIONS AND FUTURE WORK

This preliminary study demonstrates that a neural network strategy would be an effective method for health state awareness of helicopter blades. Under the studied conditions, a neural network with three hidden layers and three input parameters was able to correctly identify the health state of an aluminum beam with 100 percent accuracy. However, this study only used highly exaggerated faults for classification. In addition, the experimental setup did not allow for the monitoring of changes in the displacement of the free-end through base excitation. This parameter should be useful for detecting damage precursors. Furthermore, this study was unable to examine data from the second and third modes of vibration which may be used to identify crack location. Future work will include training the neural network with these additional parameters as well as a wide range of fault types, locations, and sizes in order develop a hierarchical control system that assesses the prognosis of the fault and applies proper counter measures in order to prevent further fault propagation and exacerbation. In order to achieve this a highly hardware redundant system consisting of several sensors (strain gauges, piezo electric transducers, accelerometers, and fiber optics) will be used to characterize faults but also predict propagation.

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