Training Feedforward Neural Networks for Structural Health Monitoring of an Aircraft Structure

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Abstract. In the past decades, structural health monitoring (SHM) has become an emerging research area for globally monitoring expensive aircraft and bridge structures. This paper presents the application of stochastic fractal search (SFS) algorithm and its chaotic-enhanced variants to train feedforward neural networks (FNNs) for monitoring an aircraft structure based on vibration data. An experimental spectral testing was carried out to obtain the normal and damaged condition data of a laboratory stiffened panel structure which imitated wingbox of an aircraft. Added mass as pseudo-fault was employed to simulate damage condition with three different damage levels at three different locations. Vibration signature features were generated based on measured frequency response functions (FRFs) and principle component analysis (PCA). Then, metaheuristic-based FNNs approach were applied to localize and predict the severity of damage on the structure. The results reveal that the proposed approach produces high classification and localization accuracy as parameters of the FNNs were optimized systematically using metaheuristic algorithms. In conclusion, the Sine chaos-enhanced SFS algorithm highlights better convergence performance and results accuracy compared to other contested metaheuristic approaches.

1. Introduction

Structural Health Monitoring (SHM) can be referring as the process of implementing a damage detection strategy for engineering infrastructures such as aerospace, civil and mechanical structures [1]. This process involves essentially 3 main stages which are:

- Surveillance of dynamical response measurement of structure periodically over time
- Feature extraction and selection of damage sensitive traits
- Determination of present condition of structure health using statistical analysis based on selected feature/s

Implementation of SHM technologies can bring benefits in terms of increasing economic outputs by minimizing failures incidence, reducing maintenance expenses, increasing the efficiency of inspection and most importantly preventing catastrophic failure that can lead to loss of life. SHM strategies possess two main approaches which are model-based and data-driven approaches. The latter approach has advantages over the former with regard to accuracy and less complexity.

As vibration-based SHM can be treated as a pattern recognition problem, several machine learning approaches have been employed i.e. artificial neural networks (ANNs), support vector machines (SVMs), k-nearest neighbours (k-NN) and many more. The feedforward multilayer perceptron (MLP)
neural networks is a popular example of ANNs categories to solve pattern recognition problems [2]. However, training neural networks in order to find best set of weight and bias parameters to the problem is a very challenging and hard process as entangled with many local optimal [3]. Thus, many metaheuristic optimization approaches were employed to train ANNs for clustering and regression problems.

In this paper, training a feedforward neural networks (FNNs) classifier model using stochastic fractal search (SFS) optimization algorithm and its chaotic variants is proposed. The rest of the paper organized as follows; Section 2 shows the experimental setup and vibration data collection of an aircraft structure for SHM. The metaheuristic algorithms to train FNNs model is explained in details in Section 3. Section 4 discussed and summarized the results before conclusions are drawn in Section 5.

2. Experimental Setup
The wingbox structure was constructed by using an aluminium sheet (750 x 500 x 3 mm) as upper surface, two ribs composed of C-channel riveted to the short edges and two stiffening L-shape stringers that secured with bolts along the length of the sheet. The wingbox structure is shown in Figure 1. Free-free boundary conditions are approximated experimentally by suspending the wingbox from a substantial frame using springs and nylon line attached at the corners of the top sheet.

The acquisition system used during the test was a DIFA SCADAS III controlled by LMS software running on a Dell desktop PC. The SCADAS III is an 8-channel, portable and high-speed data acquisition system. All measurements were recorded within a frequency range of 0-1024 Hz with a resolution of 0.25 Hz. Then, the wingbox was excited with a periodic chirp signal through a shaker at location A (80, 250) and the responses were measured using three unidirectional PCB resonant piezoelectric accelerometers attached vertically at three different locations shown in Figure 2. The damage states were introduced by using added mass bolted to the front stringer [4]. The $Hv(w)$ estimator is used throughout all the testing.

Figure 1. The experimental setup
The test order for the programme and configuration was as follows:

- Normal Condition
- 10g Mass Added at Location 01
- 30g Mass Added at Location 01
- 50g Mass Added at Location 01
- Normal Condition
- 10g Mass Added at Location 02
- 30g Mass Added at Location 02
- 50g Mass Added at Location 02
- Normal Condition
- 10g Mass Added at Location 03
- 30g Mass Added at Location 03
- 50g Mass Added at Location 03
- Normal Condition

Each configuration consisted of a clean signal acquired using 40 averages, to be used as a reference for the features selection as shown in Figure 3. Spectral lines between 187 to 194 Hz were selected from each accelerometer as input feature to the FNNs classifier.

Figure 2. Location of the excitation and sensors (top view)
Figure 3. Selected input features

For each configuration, the data were copied and then corrupted with Gaussian noise with variance of 0.0025 to produce another 100 observations data. Figure 4 shows the 3-D visualization of all data using Principal Component Analysis (PCA). All undamaged condition is clearly separable with the damage condition introduced. However, the observation of damage data was mixed especially for damage at location 01 (black) and location 03 (green).

Figure 4. The 3-D visualization using the first three principal components
3. SFS-based FNNs Classifier for SHM

The process of training FNNs model mainly consists of determining the weight and bias parameters between the neurons by minimizing the error between actual and predicted outputs. Figure 5 shows three layered FNNs with one hidden layer employed in this study. The first layer is called input layer, while the last layer is called the output layer. Other layers between the input and output layers are called hidden layer. Each layer contains neurons. The neurons in input layer are connected to neurons in hidden layer. And, the hidden layer with output layer. In FNNs, the information moves in only one-way and one-directional connections between their neurons. Information flow from input layer to output layer is achieved by hidden layers using weight and bias parameters. Each weight determines the influence of an input on the neuron and bias controls the amplitude of the output of the neuron.

![Feedforward neural networks with one hidden layer](image)

Figure 5. Feedforward neural networks with one hidden layer [5]

The mathematical expression of summation function of an FNNs is as shown in Eq. (1).

\[ S_j = \sum_{i=1}^{n} w_{ij} I_i + \beta_j \]  

(1)

where \( w_{ij} \) is the connection weight the input \( i \) and neuron \( j \), \( \beta_j \) is the bias term of the neuron, \( n \) is number of inputs. A sigmoid function usually employed as activation function as in Eq. (2).

\[ f_j(x) = \frac{1}{1+e^{-S_j}} \]  

(2)

Eq. (3) expressed the final output of the FNNs where \( m \) is the number of hidden neurons and \( W_i \) is the connection weight between neuron \( i \) and the output neuron. \( \beta_{m+1} \) is the bias of the output neuron.

\[ \hat{y} = \sum_{i=1}^{m} W_i f_i + \beta_{m+1} \]  

(3)

Finally, the learning error, \( MSE \) between actual and predicted output is calculated as fitness function for metaheuristic algorithms as in Eq. (4) where \( p \) is the number of outputs, \( o_i \) the actual output and \( \hat{o}_i \) is the desired output.

\[ MSE = \sum_{i=1}^{p} (o_i - \hat{o}_i)^2 \]  

(4)
4. Implementation and Results
An FNNs model with 4-15-10 structure was employed in the study. The first four principle components were selected as input to the FNNs model and ten classes of wingbox condition as its output. The computing platform of a Dell desktop PC with Intel Xeon 3.4 GHz CPU, 8 GB RAM, a window 7 operating system with the Visual Studio 2010 and MATLAB 2014a development environment was used in all calculation. The weight and bias parameters of the FNNs model were optimized using stochastic fractal search (SFS) algorithm and its two chaotic variants which are enhanced using Gauss/mouse and Sine maps. The more details regarding the SFS algorithm and its improved chaotic version can be referred in [6, 7]. The FNNs model was trained for ten independent runs using these three metaheuristic algorithms. The data was divided into two groups which are training (60%) and testing (40%).

Figure 6 shows the convergence curve of metaheuristic algorithms in training the FNNs model over 1000 iterations. The Sine-SFS algorithm outperformed standard SFS and Gauss/mouse-SFS in terms of average and best achieved MSE. The performance comparison of SFS and its chaotic variants in clustering the damage location and severity of wingbox is highlighted in Figure 7. The best results are indicated in bold type. Both chaotic variants of SFS algorithm achieved 92.31% of best classification accuracy in comparison to standard SFS (84.62%). In regarding the average accuracy for 10 independent runs, the Sine-SFS algorithm yield better results compared to other, as tabulated in Table 1. On the other hand, the original SFS algorithm has lowest standard deviation.

![Convergence curve of SFS algorithm and its chaotic variants](image)

**Figure 6.** Convergence curve of SFS algorithm and its chaotic variants
Based on the obtained results, the Sine-SFS algorithm possesses better searching capability in comparison to standard SFS and Gauss/mouse-SFS algorithms in training the FNNs model.

5. Conclusion
The weight and bias parameters selection of an FNNs has great influence to its performance. This study presents newly implemented stochastic fractal search (SFS) algorithm and its two chaotic variants to optimize the parameters of FNNs for SHM of an aircraft structure with their performance evaluation in terms of convergence speed and classification accuracy. The Sine-SFS algorithm highlights better convergence performance and results accuracy compared to other approaches. The proposed method will be employed to classify damage condition of real aircraft structure in future study.

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