

Data-Driven Source Localization of Impact on Aircraft Control Surfaces

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Abstract—Aircrafts are potentially subjected to damaging events during their service life. How to cope with impact events and impact related damage is a priority in the development of aircraft composite structures. The impact monitoring method presented in this paper utilizes acoustic emission (AE) based data to classify and thereby localize impact events. The method is implemented and tested on a full-scale aircraft elevator. This work builds on earlier research for the classification of AE signals acquired by a single sensor during impact events using a backpropagation neural network with two hidden layers [1]. The innovative aspect of the new method lies in the use of a deep learning algorithm to achieve the zonal localization of impact events. Compared to the backpropagation neural network method, the deep learning method can output localization results with improved accuracy without the need to extract signal features, such as time of arrival, signal strength and amplitude. For this paper, stacked autoencoder algorithms were applied. To train and test the performance of the new model, the same aircraft elevator impact test setup from prior work was used. A single sensor was attached to the spar of the elevator to collect the acoustic emission events. Impacting with steel spheres was conducted on the elevator skin at various distances from the impact source to the sensor. Results demonstrate the efficacy and potential of the deep learning-based approach for localization of impact events for aircraft elevators.

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1. INTRODUCTION

Commercial aircrafts may suffer many impact events during normal operation. In some cases, associated damage could accumulate and cause a decrease in the fitness for service of the aircraft structure. Timely maintenance and repair are necessary for the continued safe operation of the aircraft. Traditional structural inspections for aircraft are generally simple visual inspections followed by more comprehensive and detailed inspections at scheduled intervals [2]. In-flight monitoring systems can be utilized to assure the timeliness of visual inspections and to inform focus areas for more detailed nondestructive evaluations. It is not necessary that such systems provide information in real-time, rather the data gathered may be downloaded and interpreted between flights. Such systems, once proven effective, may be exploited to extend the time between visual and/or more detailed nondestructive evaluations.

Acoustic emission (AE) has been widely utilized for the detection and assessment of damage in composite materials [for example, 3-9], including aircraft applications [for example, 10-12]. Marantidis et al. [10] developed a smart structure health monitoring system for military aircraft. Geng et al. [11] investigated the evaluation of fatigue damage on aircraft structures by using the AE technique. Diamanti et al. [12] utilized AE to detect and localize impact damage in aircraft composite components. However, most of these avenues of research were conducted on small-scale lab specimens and did not study the problems related to real-time

in-flight health monitoring based on AE. To further investigate this problem, an AE based passive structure health monitoring system for aircraft elevators was proposed by Soltangharaei et al. [1] to detect and localize the damage impact on aircraft elevators during flight. A single AE sensor was attached to collect acoustic emission signals during impact events. Features like rise time, signal amplitude, and time of arrival were extracted from the raw signals as the input training dataset of a backpropagation neural network (BP neural network). The output of the neural network is the zone corresponding to the AE source. The results show that the proposed passive structure health monitoring system is reliable and has high accuracy in impact zonal source localization.

The artificial neural network proposed above is a traditional shallow neural network. Before training and testing, feature extraction of the collected data and selection of appropriate features for training are necessary. This usually relies on experience. Moreover, the traditional neural network has difficulty controlling the convergence, which easily causes an optimal local solution. When the network has more than four layers, it is difficult to optimize the whole network with the gradient descent method because of the vanishing gradient problem and the exploding gradient problem [13]. Hinton et al. [14] formally proposed the concept of deep learning. A detailed solution to the vanishing gradient problem was proposed as use of the greedy layer-wise training algorithm through unsupervised learning methods, and then the supervised backpropagation algorithm for tuning. The main advantage of deep learning over conventional neural networks is that the input dataset for deep learning could be raw data without a need to extract features. In deep learning methods, AE waveforms could be utilized as the input dataset of the training procedure. In recent years, deep learning has been successfully applied in the field of AE monitoring [for example, 15-18]. Li et al. [15] proposed an AE based gearbox fault diagnosis method using deep random forest fusion. He et al. [16] utilized a deep learning method to diagnose bearing

fault by classifying AE signals. Shevchik et al. [17] developed an in-situ quality monitoring system in additive manufacturing using the AE technique. A spectral convolutional neural network approach was proposed to classify the acquired AE data. Ebrahimkhanlou et al. [18] proposed a deep learning framework for AE source localization in metallic plate-like structures. These researches show the benefits and potential of the application of deep learning in AE monitoring. To the best of the authors' knowledge, little research has applied deep learning in AE real-time monitoring on aircraft structures. To fill this gap, an improved deep learning based passive structure health monitoring system for aircraft elevators was developed. The zonal localization method in the previous work [1] was improved by using stacked autoencoder neural networks. The results show that the improved system has a higher accuracy in the classification and localization of the AE events.

2. DEEP LEARNING BASED PASSIVE STRUCTURE HEALTH MONITORING SYSTEM

Improved passive monitoring system

This study developed an improved deep learning based passive monitoring system based on previous research [1]. The system contains an in-flight phase and an after-flight phase. The procedures for in-flight detection and after-flight analysis is shown in Figure 1. For the in-flight phase, an AE sensor mounted on the spar of the elevator, records impact events continuously during flight. AE signals are filtered through a bandpass filter in a preamplifier. The filtered signals are sampled and stored in the system. The AE signals are used as inputs for the first deep neural network (after-flight phase). The signals will be classified based on whether the impacts are on ribs or panels. After the classification is completed, the data corresponding to each class will be input to the next deep learning neural network to determine the zonal location of each impact event.

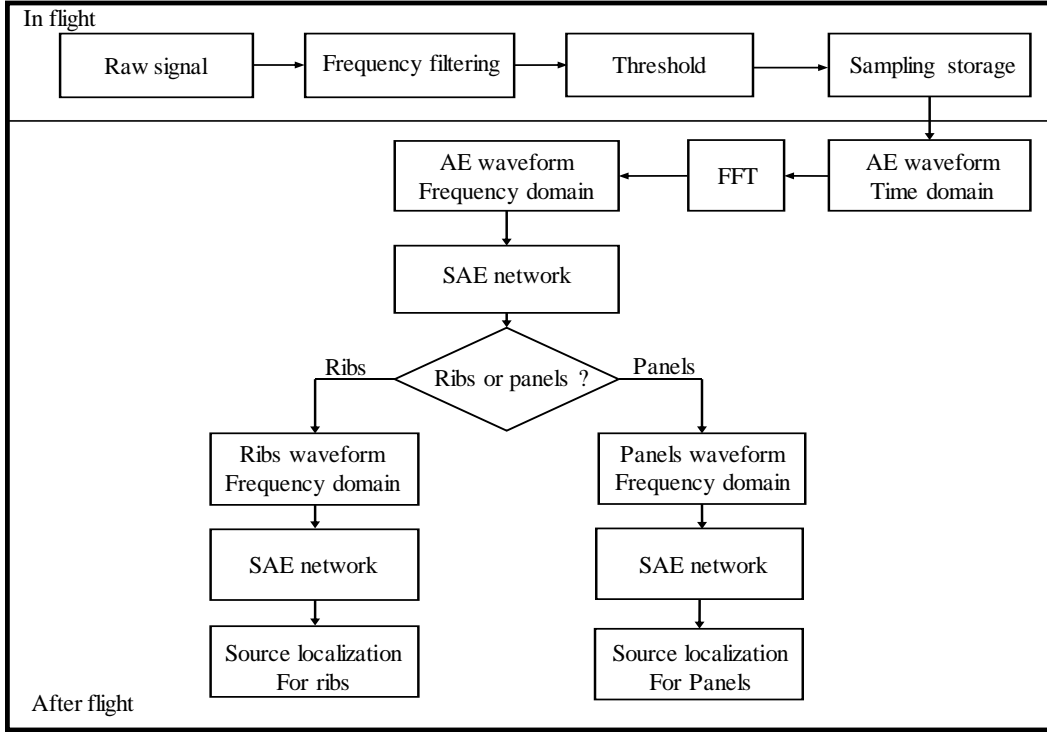


Figure 1. Impact localization flowchart

Stacked autoencoder

An autoencoder is a three-layer neural network that learns the characteristics of the input data by how close the target output is to the input data [19]. By making some restrictions on the hidden layer, such as reducing the number of neurons, the network is forced to compress the data and try to reconstruct the input data. The compression process is unsupervised and compressed data are the features extracted from the input data. Figure 2 shows a typical autoencoder.

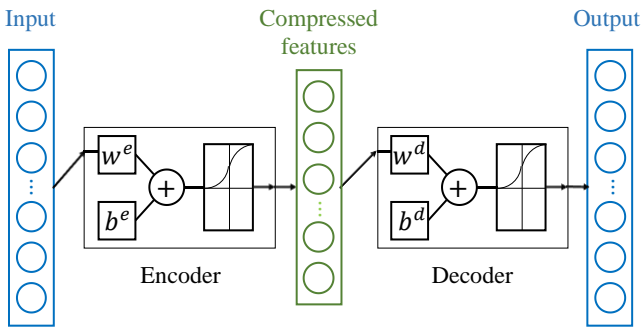


Figure 2. Typical autoencoder

The stacked autoencoder (SAE) neural network is a deep neural network composed of multiple layers of autoencoders proposed by Bengio et al. [20]. The output of the previous autoencoder is used as the input of the subsequent autoencoder.

The data set being input into the stacked autoencoder is defined as a vector $\{x^1, x^2, x^3 \dots x^n\}$. The number of the data is n , the dimension of each input is m . x^i is the i th input vector. The encoding process is used to transfer sample x from the input layer to the hidden layer. Using the activation function, an m -dimensional vector is mapped into a k -dimensional vector. Equation (1) shows the mapping process.

$$G = f(w_{(i)}^e x^i + b_{(i)}^e) \quad (1)$$

Where G is the k -dimensional compressed feature code, x^i is the i th input sample, $w_{(i)}^e$ is the encoding weight, $b_{(i)}^e$ is the encoding bias. f is the activation function. The activation function for the autoencoder in this paper is a sigmoid function, which is shown in Equation (2)

$$f(x) = \frac{1}{1+e^{-x}} \quad (2)$$

The decoding process is used to transfer the compressed feature code from the hidden layer to the output layer. The k -dimensional vector G is mapped to the m -dimensional output vector \hat{x} as shown in Equation (3).

$$\hat{x}^i = f(w_{(i)}^d x^i + b_{(i)}^d) \quad (3)$$

Where \hat{x}^i is the m -dimensional output vector, $w_{(i)}^d$ is the decoding weights, and $b_{(i)}^d$ is the decoding bias.

The training goal of the autoencoder is to find a set of optimal network parameters $w_{(i)}^e, b_{(i)}^e, w_{(i)}^d, b_{(i)}^d$ to minimize the error between the input and output data. The error can be expressed

by the mean squared error loss function, as shown in Equation (4) and Equation (5).

$$L = \frac{1}{n} \sum_{i=1}^n J(x^i, \hat{x}^i) \quad (4)$$

$$J^i = \frac{1}{2} \|x^i - \hat{x}^i\|^2 \quad (5)$$

Where L is the sum of the error between all the input and output data. J^i is the mean squared error between input x^i and output \hat{x}^i . Each autoencoder network reaches the minimum amount of errors by backpropagation and the gradient descent method. When the L value in the current state is obtained, the system will judge whether L has reached the expected minimum value. If L reaches the value, the autoencoder network training is completed, and if not the residuals of each neuron are output to update weights and bias parameters.

During the training process, each autoencoder is trained separately. Once an autoencoder is trained, the compressed features obtained from this autoencoder is used as the input of the next autoencoder. After training, a supervised softmax layer is utilized to classify the final compressed features. The final features and their corresponding inputs are divided and mapped into several classes. Figure 3 shows the procedures of an SAE. The last step of SAE is fine-tuning after all the layers in the network are trained. Fine-tuning is an optimization strategy for deep learning that updates the weights and biases of an entire deep learning network.

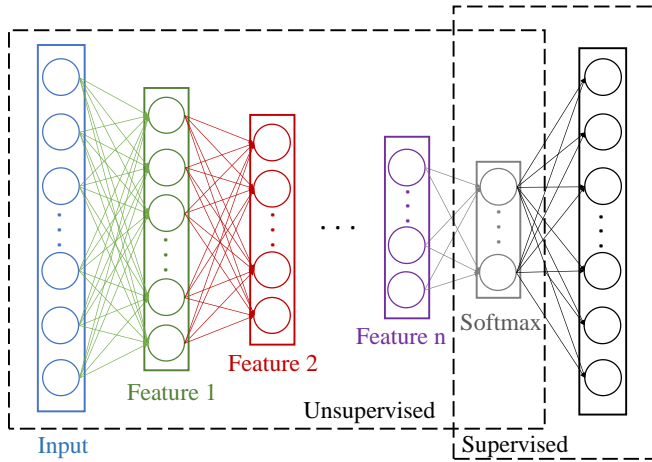


Figure 3. A stacked autoencoder composed of n layers

3. EXPERIMENTAL DESCRIPTION

Test setup

To verify the effectiveness of the deep neural networks, a steel ball impact test was conducted on a real sized aircraft elevator (Figure 4). The dimension of the elevator is shown in Figure 5. The elevator was installed on a steel frame which was made of 5-inch mild steel channels (240 inches long \times 24 inches high). A turnbuckle was used to apply bending in the elevator to simulate the flexure of the horizontal tail during flight.

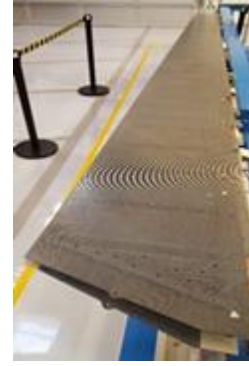


Figure 4. Elevator specimen

Steel ball impact experiment

The impact test was performed on the elevator, and the AE data obtained was used to train the SAE required by the passive monitoring system. The steel ball used in the experiment was 1/2 inch in diameter. The drop height of the steel ball is kept constant at 2 feet. The elevator has 20 ribs. Three impact points were marked on each rib and one impact point was marked on the panel (the area between ribs). Each point was hit 60 times by the steel ball. In total, 3600 impacts were conducted on ribs, 1200 impacts were on panels (Figure 5).

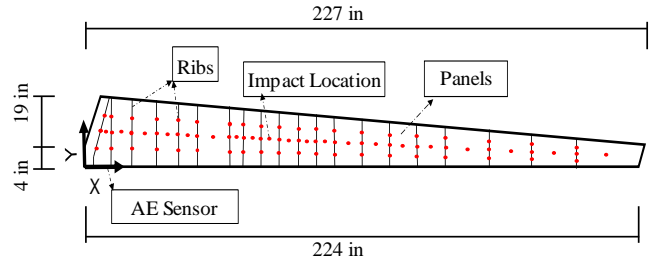


Figure 5. Impact and sensor locations

Acoustic Emission Instrumentation and Setup

A PAC Micro-30 sensor was attached to the location shown in Figure 5. The hardware and software of the system are manufactured by the Physical Acoustics Company. AE data are acquired using a 16-channel PCI DISP system. The pre-trigger time, which recovers acoustic waveform prior to the threshold crossing, was set to 256 μ s. The sampling rate was set to 5MHz (or 5,000,000 acoustic samples per second). The duration was set to 2000 μ s. The time from threshold crossing to peak amplitude, called the peak definition time, was set to 200 μ s. The hit definition time, which determines when to stop recording a hit and is typically twice the peak definition time, was set to 400 μ s [21]. Lastly, the hit lockout time, which prevents recording late-arriving signals and reflected hits, was set to 400 μ s.

4. RESULTS AND DISCUSSION

Deep learning based passive monitoring system

The deep neural network applied in this paper is the SAE network with two autoencoder layers. The first autoencoder has a hidden size of 100, The second autoencoder has a hidden size of 50. The input data of the network is the raw AE waveforms of 4800 impacts (3600 on ribs and 1200 on panels). The outputs of the second autoencoder are the final features. The softmax layer is a supervised classification layer. The input data is the final features coming from the second autoencoder. As mentioned in the after-flight analysis of the passive monitoring system, the first deep learning network classifies the AE events by the boundary conditions (ribs or panels), the labels used in this network are the boundary conditions of the corresponding event. For the next zonal localization deep learning network in the system, the labels are zone numbers attributed to each of the AE events. Figure 6 shows the SAE networks applied in this paper.

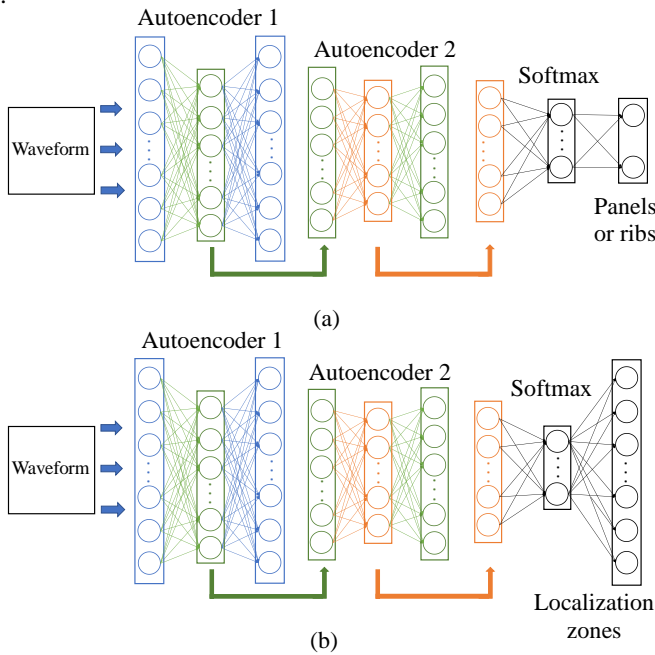
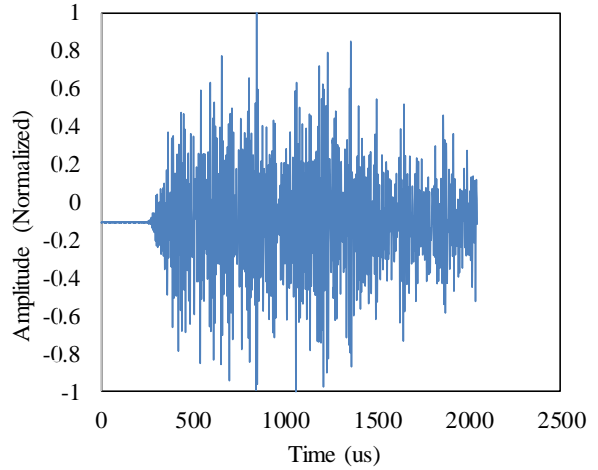


Figure 6. An SAE with two autoencoders and a softmax layer: (a) Boundary conditions classification network; (b) Impact source localization network

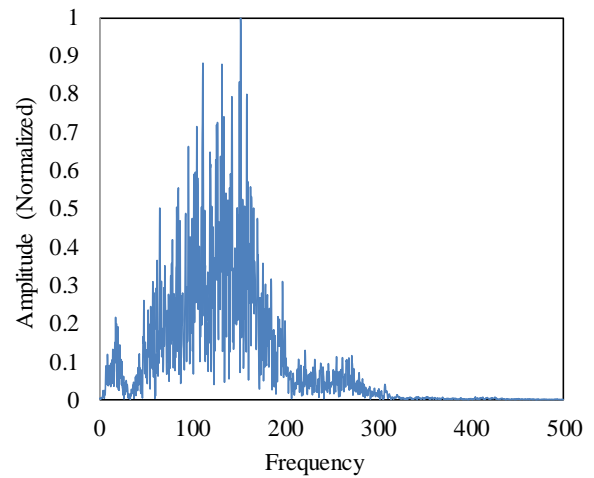
Input preparation

The input data for the neural network proposed above is a vector. It could be the raw AE time domain waveform and its frequency domain magnitude. A typical AE time domain waveform of impacts and its Fast Fourier Transform magnitude are shown in Figure 7. In order to verify the accuracy of the two input datasets, the waveforms in both time and frequency domains were prepared as input data for training. Labels were prepared according to whether an impact occurs on the rib or panel (Figure 6a). 66.7% of the data was used for training, and 33.3% was used for testing.

After several trainings, the optimum results are as shown in Figure 8.



(a)



(b)

Figure 7. Typical waveform: (a) Time domain; (b) Frequency domain

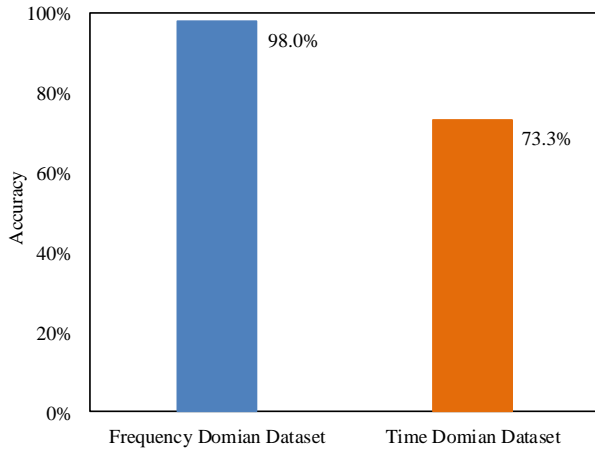


Figure 8. Accuracy of the SAE network trained by two types of inputs

The SAE network trained with the frequency domain dataset has an average accuracy of 98%. The network trained using the time domain dataset has an average accuracy of only 73.3%. The reason for the low accuracy of time domain dataset might be that the time domain waveform not only has the AE information but also contains a large amount of low-frequency vibration information that is irrelevant to AE but might affect the network performance. The frequency domain dataset contains multimodal and dispersive characteristics of AE, which increases the efficiency of the network performance [22]. Thus, a network with a frequency domain magnitude as a training dataset can obtain higher precision results. Therefore, the frequency domain magnitude was utilized as input datasets for the rest of the paper.

SAE for boundary conditions classification

To test the accuracy of this network. The 4800 impact events were used as the input dataset. 66.7% of them were used for training, and 33.3% were used for testing. Labels were prepared according to the boundary conditions of events. The accuracy for boundary conditions classification is 98.0%, as shown in the confusion matrix (Figure 9).

Estimated	Actual		
	Rib	Panel	
Rib	1184 74.0%	16 1.0%	98.7% 1.3%
Panel	16 1.0%	384 24.0%	96.0% 4.0%
	98.7% 1.3%	96.0% 4.0%	98.0% 2.0%

Figure 9. The results of the SAE in classification of the boundary conditions

SAE for source localization

After classifying based on boundary conditions, the dataset was separated and transferred to the SAE networks for zonal source localization (Figure 6b). The number of layers and neurons for the zonal source location networks is the same as the networks in the previous section. The only difference is labeling for the softmax layer. The labels are zone numbers attributed to each AE event. The outputs are vectors which show the corresponding zones of events. The accuracy of the network depends on the number of zones.

Three zones source localization

The previous research utilized a BP neural network to localized impact events. The locations of the impact events were divided into three zones. [1]. The same divisions of zones were considered in this paper. Figure 10 shows the zonal divisions. 66.7% of data and 33.3% of data were used for training and testing, respectively. The accuracy for the three-zone impact localization is 99.2%, as shown in the confusion matrix (Figure 11). The accuracy of three-zone source localizations for the BP and SAE are shown in Figure 12.

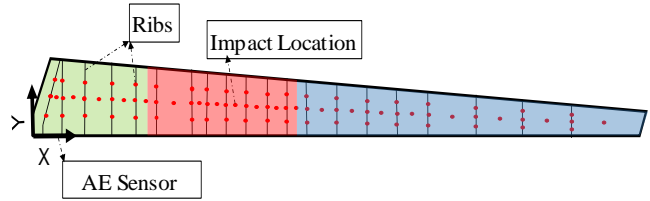


Figure 10. Three zones

Estimated	Actual			
	Zone 1	Zone 2	Zone 3	
Zone 1	298 29.2%	0 0.2%	0 0.0%	100% 0.0%
Zone 2	1 0.1%	418 41.0%	4 0.4%	98.8% 1.2%
Zone 3	1 0.1%	2 0.2%	296 29.4%	99.0% 1.0%
	99.3% 0.7%	99.5% 0.5%	98.7% 1.3%	99.2% 0.8%

Figure 11. The confusion matrix of the SAE in three zone impact localizations for ribs

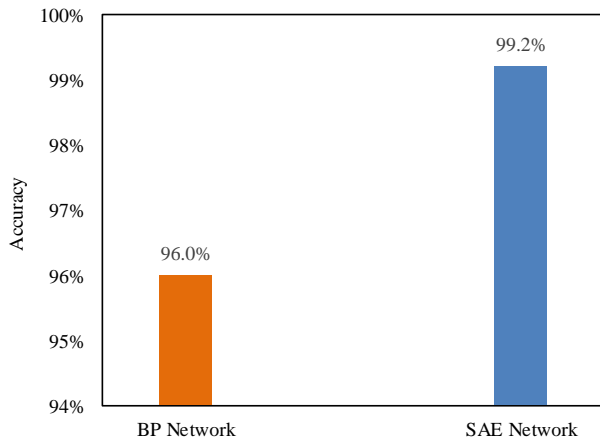


Figure 12. The comparison of accuracy in three zone localizations

Based on the results from the previous research. Without considering the overlap on the boundaries, the accuracy of the three-zone localization results from the BP network was 96.0%, which is less than the accuracy of SAE. This indicates that SAE has a better performance than the BP neural network.

Twenty zone source localizations

To further investigate the performance of the SAE source localization network when a larger number of zones is applied. A similar procedure was conducted on the impact data to train a network for twenty zones (each zone contained a rib/panel section). 66.7% of data was used for training, and 33.3% was used for testing. The average accuracy of the network for the impacts on the ribs is 94.7% and 92.5% for the impacts on the panel, both of which are acceptable in 20 zone localizations. These results are shown in Figure 13 and Figure 14.

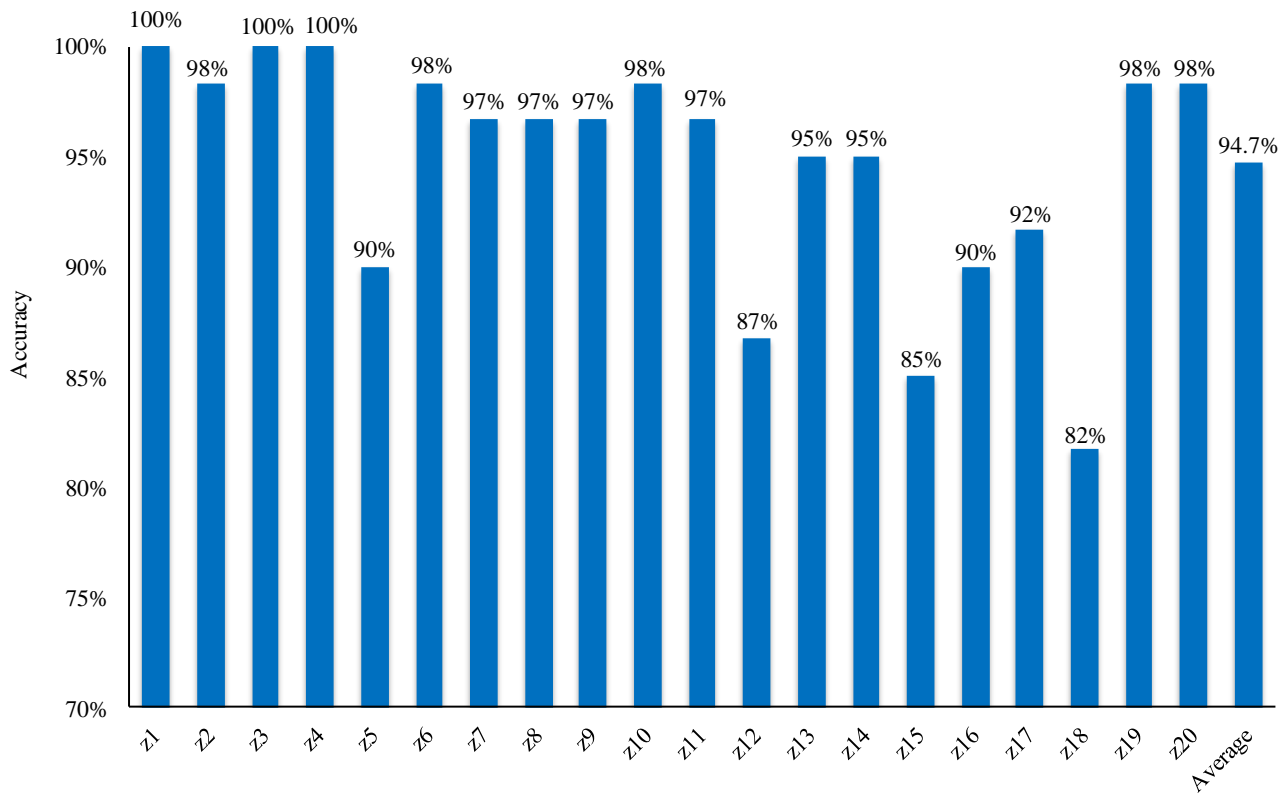


Figure 13. Accuracy of twenty zone localizations for ribs

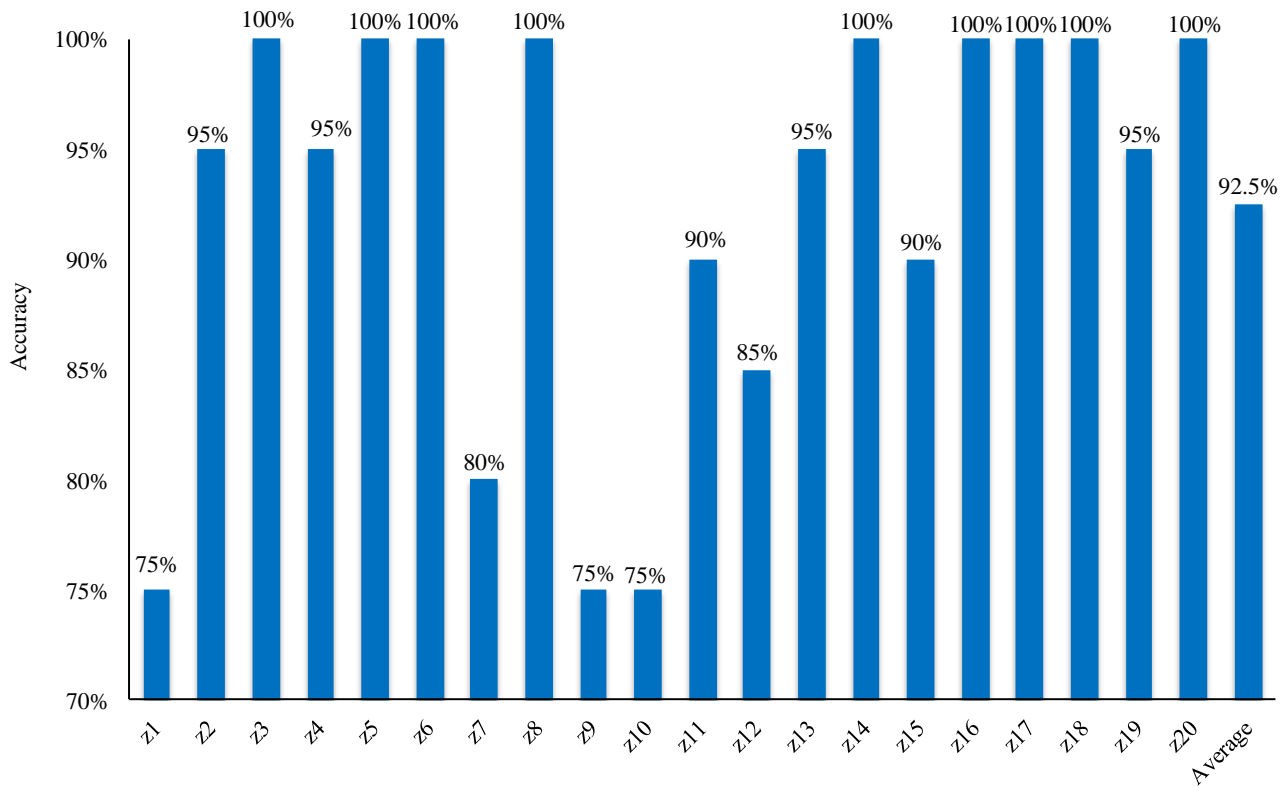


Figure 14. Accuracy of twenty zone localizations for panels

5. CONCLUSIONS

An AE-based passive monitoring system was developed using deep learning neural networks. The performance of the system was tested on an aircraft elevator with a single AE sensor attached on the spar. To validate the efficiency of the trained network (SAE), several impacts were conducted. The accuracy of the trained networks were compared using time and frequency domains. The performance of a BP neural network was compared with the SAE neural network. Finally, the accuracy of zonal source localizations for the SAE networks with three zones and twenty zones was compared.

Pertinent conclusions are:

1. Frequency domain waveforms are more suitable as neural network input datasets than time domain waveforms, since the time domain waveform contains a large amount of complex vibration information which may reduce the neural network performance.

2. The SAE network has better accuracy than the traditional BP neural network in the zonal source localization of the impacts on the aircraft elevator.
3. The SAE network has reasonable accuracy for impact localizations on the aircraft elevator even if a larger number of zones are used.

Further work could be an investigation of the effect of impact energy, impactor size, and material on the performance of network. Other advanced deep learning algorithms like deep belief networks and convolutional neural networks could be applied to this system.

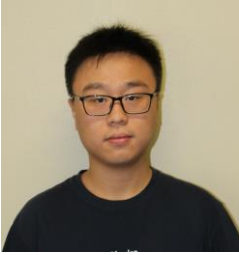
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BIOGRAPHY



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