A Minimally Intrusive Impact Detection System for Aircraft Moveable using Random Forest

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ABSTRACT

Abstract: Impact events are of interest during the service life of commercial and military aircraft and reliably assessing the location of impact damage is important for aircraft maintenance. Traditional impact detection for aircraft is generally confined to visual inspections between the flights intermittently followed by more comprehensive and detailed inspections. The purpose of the study described herein is to investigate a path forward for the automated detection and localization of impact events. Machine learning is investigated as a means to improve upon traditional inspection methods. A flight amenable impact monitoring system was developed and utilized to detect and localize impact events on a thermoplastic aircraft elevator in a laboratory setting at the McNAIR Aerospace Center. Steel spheres were dropped from a controlled height on the elevator skin to simulate damaging events that may occur during flight. To keep weight, power, and cabling to a minimum a single sensor was attached to the spar of the elevator. A source localization approach based on random forest is proposed. Several features were extracted, and feature importance was ranked using random forest. The selected features were gathered as a dataset to train and test the performance of the proposed source localization approach. Results demonstrate the efficacy and potential of the random forest-based approach for localization of impact event monitoring for the application of a thermoplastic aircraft elevator.

Keywords: Acoustic emission, Source localization, Random forest
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1. INTRODUCTION

Aircraft structures are exposed to impact damage during their service life caused by debris and hail. The primary design concern in composite structures is the resistance of layered surfaces against accidental damage such as impact. Therefore, the localization and damage quantification of damage impacts should be studied and considered to guarantee flight safety and prevent severe structural failure. Since the aircraft structural components are large scale, the visual inspection and monitoring of them are challenging and subject to human errors. A real time health monitoring system can be applied to automatically recognize and localize the impact damage instead of manually inspection.

Acoustic emission (AE) is a promising nondestructive structural health monitoring technology which can be applied on the impact monitoring of aircraft. This method is sensitive and has continuous monitoring capabilities [1-3]. It has been widely used for the detection and evaluation of composite damage [for example, 4-10]. Ono et al. [4] evaluated the damage of carbon fiber reinforced polymer (CFRP) plates under dynamic load using AE signals, Impact tests were conducted on four types of CFRP plates with a steel sphere. AE sensors were attached on both surfaces of the specimens. The results indicated that several failure modes were detected under dynamic loading in comparison to quasi-static loading. Matrix crack propagation was the dominated failure mode, while other failure modes such as delamination could not be discerned clearly. Marec et al [5] identified the damage mechanisms in polymer-based composite materials by using AE monitoring. A three-point bending test was performed on a fiber-matrix composite specimen, while two AE sensors were applied for signals collection. Unsupervised pattern recognition analysis and principal component analysis (PCA) were utilized for classification of the AE signals. The classification results performed a good correlation to the damage mechanisms of the composite specimen being monitored. Liu et al. [6] studied on the failure mechanisms and damage evolution of carbon fiber/epoxy composite laminates. The acoustic emission data during tensile test was mapping with the results that watched and analyzed by scanning electron microscope (SEM). The study demonstrated that failure modes including the splitting matrix cracking, fiber/matrix interface debonding, fiber pull-out and breakage and delamination could be represented by creating true mapping based on the data recorded by AE monitoring. Whitlow et al. [7] proposed an approach for associating in situ AE detection with final failure in continuous fiber reinforced ceramic matrix composites (CMCs). Digital image correlation (DIC) was used for obtaining surface strain measurements. The results shown there was good agreement between the two techniques. Saidane et al. [8] investigated the evaluation of damage mechanisms during tensile tests in hybrid flax-glass fibres reinforced epoxy composites. AE monitoring was conducted for providing signals during the tests. Comparing with the results observed by SEM, a conclusion was made: the cumulative of AE energy could indicate the overall failure of composite. Dia et al. [9] analyzed the characterization of damages in a hybrid laminate aluminum /glass during quasi-static and fatigue tests. Principal Components Analysis (PCA), k-means unsupervised clustering analysis, classification and regression Trees (CART) were used for damage identification. Results shown it was possible to identify damage in fibre metal laminates (FML) during both quasi-static and fatigue test. Khamedi et al. [10] identified failure mechanisms of unidirectional carbon/epoxy composites by studying the wavelet packet transform of AE signal processing. AE events were recorded during tensile test. The collected AE data was converted to wavelet for comparing with SEM observations. The results of this study pointed out that the wavelet transformed from AE waveform could link to the damage mechanisms of unidirectional carbon/epoxy composites.

However, there is limited access to attach AE sensor on the aircraft. One of the main challenges to accomplish the AE-based real time monitoring is developing a method to localize the impacts with a maximum level of certainty and using a single sensor. To solve this problem. Random forest is investigated as a mean to achieve the localization of impact events

Random forest is an ensemble algorithm. By combining multiple decision trees, the final result can be voted or averaged to make the overall model results with high accuracy and generalization performance. Random forest has an advantage that the impotence of input variables can be ranked. A features selection can be conducted based on this. Random forest has been successfully applied in the fields of faults fault diagnosis based on vibration and AE signals. Cerrada et al. [11] built a robust system for the multi-class fault diagnosis in spur gears using genetic algorithm and random forest. An acceptable diagnose accuracy was obtained based on the real vibration signals. Patel et al. [12] presented random forest classifier as an approach for classification of bearing fault and features selection. The most important features of vibration signals were selected and assigned to the random forest model. Results indicated the random forest is turn out to be a suitable approach for fault diagnosis of any rotating machine. Shevchik et al. [13] utilized AE and random forest as tool to investigate the prediction of the scuffing failure in lubricated mechanical components. A good performance was observed by using wavelet-derived features as input data. Those previous research shows using random forest might be an approach to select appropriate features and improve the passive health monitoring system.

In this study, a minimally intrusive impact detection system is explored through acoustic emission monitoring and random forest model. A single AE sensor was employed to detect and collect AE data during impact. Random forest model was utilized for source localization. An impact experiment was conducted on a thermoplastic aircraft elevator in the laboratory environment to verity the efficiency of the proposed impact detection system. The results show that the impact monitoring system using AE and random forest is reliable and has high accuracy in locating the impact area.

2. METHODOLOGY

2.1 Acoustic Emission monitoring

AE is a physical phenomenon that stress waves are generated by the rapid release of elastic energy when the object is under the condition of external force or deformation. AE signals can reflect some properties of the object. By attaching AE sensors to the surface of the object, the AE signal can be detected. The technique of collecting, analyzing and using AE signals to diagnose the status of the object is called AE nondestructive monitoring. By processing the AE signal, it can be transformed into different AE features. Commonly used AE features such as “Amplitude”, “Counts”, “Energy”, “Rise time” and “Duration” are shown in Figure 1. In this study, A single AE sensor was employed to detect and collect AE data during impact. 15 features were extracted from the signals and formed an AE dataset. The source localization approach by using these AE features from one sensor is introduced in Section 2.2.

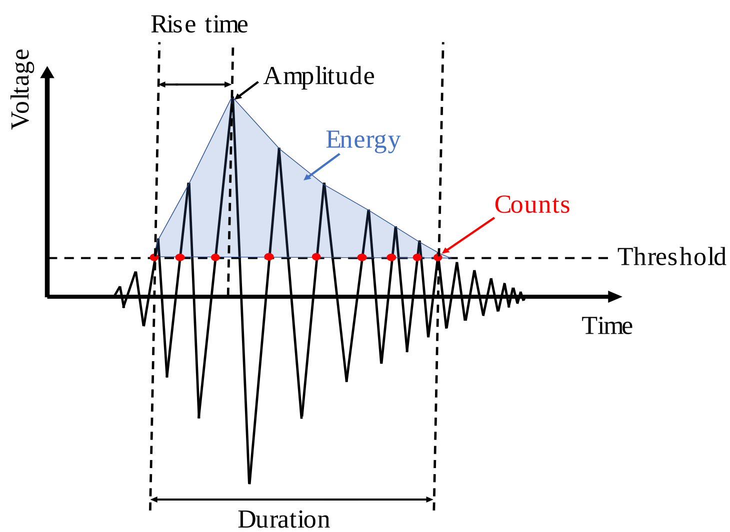

Figure 1. AE waveform and typical features

2.2 Random forest model

A random forest classification model contains 100 decision trees was utilized in this study as the approach for source localization. The AE dataset contain 15 features. They are “Amplitude”, “Count”, “Rise time”, “Duration”, “Average frequency”, “Root mean square”, “Average signal level”, “Energy”, “Absolute energy”, “Peak frequency”, “Reverberation frequency”, “Initial frequency”, “Signal strength”, “Frequency centroid” and “Counts to peak”. Those features were utilized for features selection. A ranking of the importance of features is given by random forest model. The features with the majority importance are gathered as input dataset to train and test the impact source localization random forest. The reason for conducting the feature selection is that: impacts occur frequently during the flight and the AE system collects a large amount of AE signals while the data storage space is limited. By reducing the dimension, the required storage can be saved for more AE collecting. The input dataset after feature selection is utilized to build 100 subsets by using bootstrapping method. Each subset is assigned to its own decision tree. These decision trees inside the random forest work independently and generate their own localization results. The final result (Zone number) is given by voting. Figure 2 shows the random forest used in this article. The output of the random forest model is the zone number of the corresponding AE event. The determination of zones is presented in Section 4.1

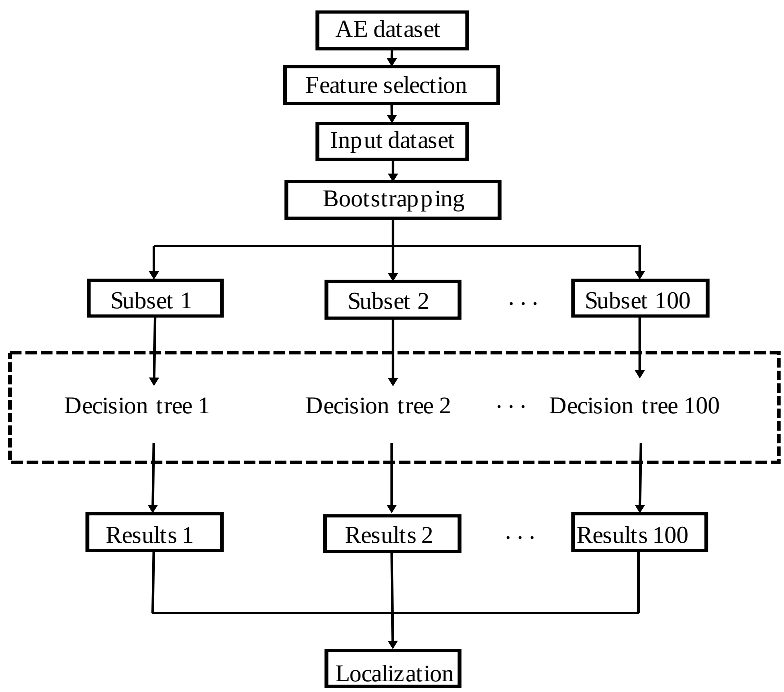

Figure 2. Configuration of random forest model

3. EXPERIMENTATION

A steel ball impact test was conducted on a real sized aircraft elevator (Figure 5) to verify the effectiveness of the source localization method using random forest. The elevator was mounted on a steel frame, made of 5-inch channels, with an overall length of 240 inches and a height of 24 inches. The hinge brackets on the elevator spar were connected to hinge points located on the frame. A turnbuckle was used to apply bending in the elevator to simulate the flexure of the horizontal tail during flight.

To collect the dataset for random forest. An impact tests were conducted using steel balls of 1/2 inch in diameter. The drop height of the steel ball is kept constant at 2 feet (Figure 3). A tube was used as a guide to control each impact's location and height.

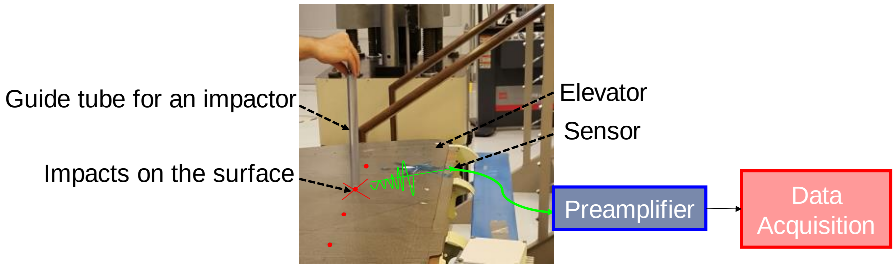

Figure 3. Steel ball dropping test

Three locations were marked on each rib. The impact locations are shown in Figure 4, marked as red points. Each location was impacted 60 times by the steel ball. An AE sensor was attached on the front spar of the elevator as shown in Figure 4.

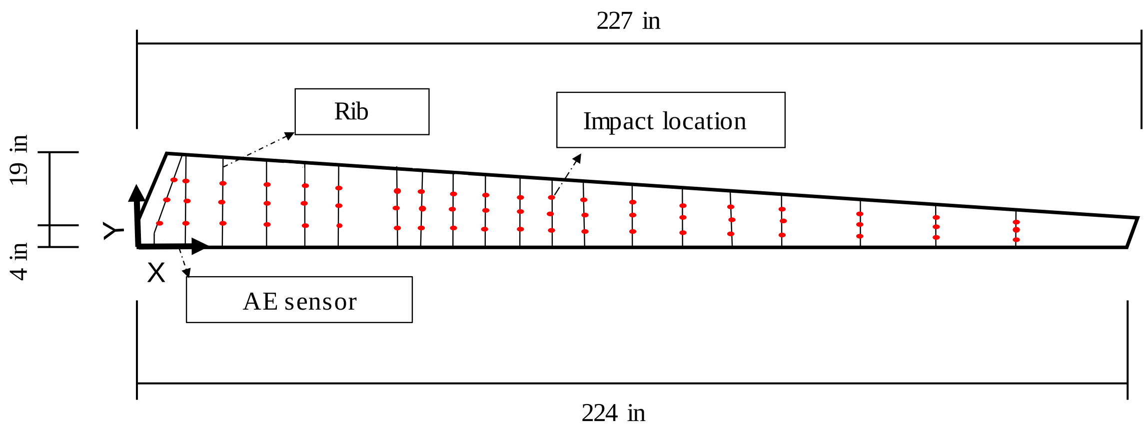

Figure 4. Impact and sensor locations

4. RESULTS

4.1 Determination of zones

As mentioned before, this study is focusing on zonal inspection. To determine the appropriate division of the zones, unsupervised pattern recognition method (k-means) was utilized for clustering the AE data. To reduce the dimension of features before sending for the unsupervised pattern recognition, a Principal component analysis (PCA) was conducted to the data. 2 principal components (PC) were utilized to present the 15 features. The data was classified into three clusters and presented in the PC space in Figure 5. This clustering was used to define the zones for the random forest model as shown in Figure 6. From left to right, the elevator is divided by zone 1, zone 2 and zone 3.

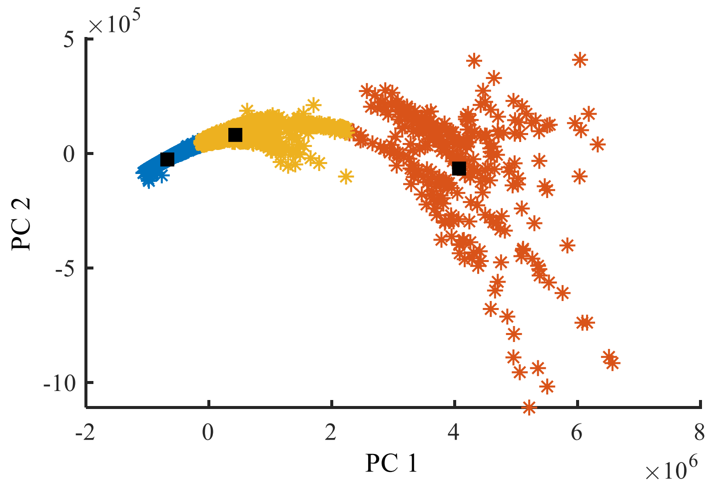

Figure 5. Clustered data in PC space

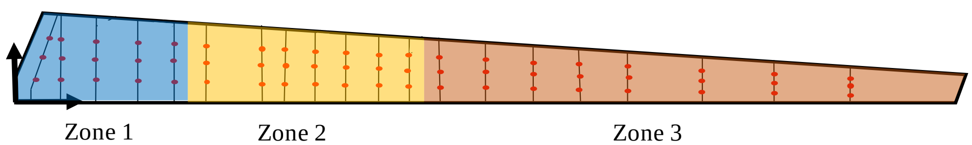

Figure 6. Zone division

4.2 Source localization

Dataset with 15 features was assigned to the random forest model as input. The ratios for training and testing dataset are 66.7% and 33.3%. The overall accuracy of impact localization is 98.33%, as shown in the confusion matrix (Figure 7). The localized accuracy of zone 1 to 3 is 98.67%, 98.33% and 98.20%. This result is compared with the case when using input dataset after feature selection. The details are shown in Section 4.3.

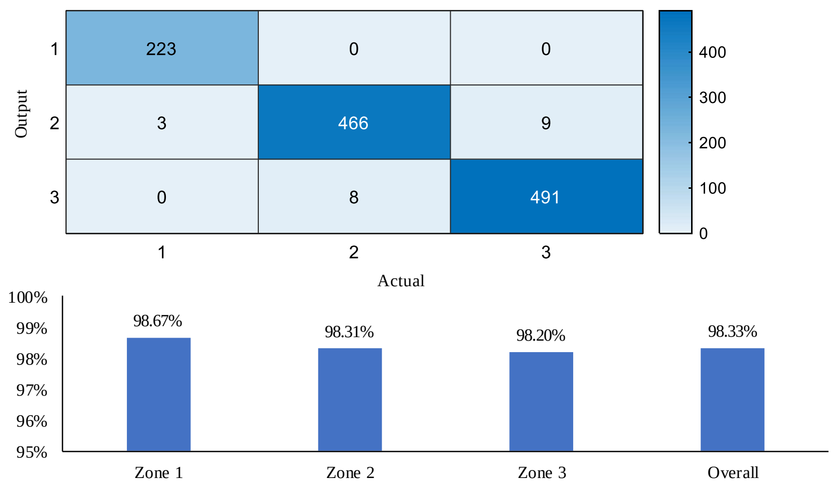

Figure 7. Accuracy of impact source localization

4.3 Features selection

By using the random forest model, this study analyzes the importance of the AE signal features. The names of these 15 features and their corresponding percentages of importance are shown in Figure 8. By observing Figure 8, it can be noticed that the features "count", "amplitude", "duration", "signal strength" and "energy" account for a large proportion of the overall importance of the feature, their cumulative importance reaches 65% out of the overall importance. Those features have a major impact on the source localization results. The importance of the rest features is relatively low. Deleting them will not have a significant impact on localization performance.

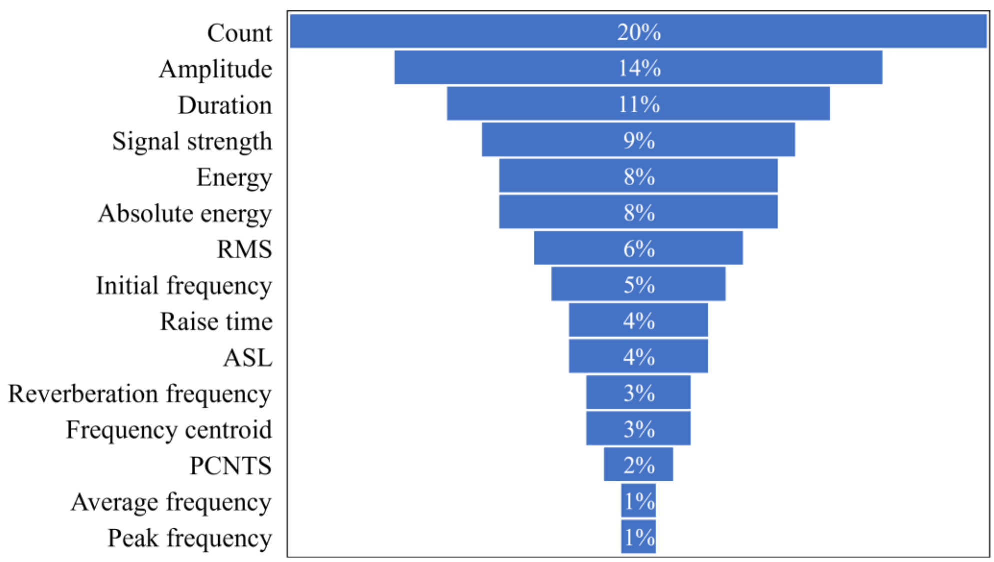

Figure 8. Ranking of the features

An input dataset made of the top 5 features was assigned to the random forest model. The localized accuracy of is 97.75%. The localization accuracy and required input storage were compared with the case when using AE data before feature selection (15 features). The detail is shown in Table 3.

It can be noticed that reducing the input dimension from 15 to 5 lead to a slightly decreasing in the accuracy of impact localization while the required storage for input decrease from 299,008 byte to 90,112 bytes. Almost 68.86% of the storage can be saved for more AE signals collection.

Table.1 Comparison of the accuracy by different input

Input	Storage (byte)	Accuracy
15 features	299,008	98.33%
5 features	90,112	97.75%

5. CONCLUSIONS

In this study, impact experiment was conducted on a real-scale thermoplastic elevator specimen. Acoustic emission monitoring was utilized to capture signals during impact. Several AE features were extracted from the acquired AE signals. Random forest model was assigned to select appropriate features and give the source localization results based on the selected features

Pertinent conclusions are:

1. By employing AE monitoring and using random forest as a source localization approach. A good performance on the impact detection and localization can be observed when a single AE sensor is used.

2. The localization accuracy decreases slightly after deleting the features with relative low importance. Meanwhile the required data storage is significantly reduced. During the flight, the AE acquisition can keep several necessary features and delete the others to save the storage space for long term monitoring.

Further work could be an investigation of the influence of the steel ball's size during the impact testing. Other advanced machine learning technique like deep learning could be investigated for the impact detection system in the future.

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