ASSESSMENT OF IMPACT DAMAGE LEVEL FOR COMPOSITE AIRCRAFT COMPONENTS USING ACOUSTIC EMISSION

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ABSTRACT

Impact is a threat to the operational safety of aircraft. A real-time intelligent impact monitoring system can supplement or potentially replace traditional visual inspections and greatly improve the efficiency of aircraft maintenance. In this paper, A smart sensing system based on acoustic emission sensors is proposed for the assessment of impact damage level and location. To meet the demands of the operational environment of aircraft, it is desirable to employ a minimal number of acoustic emission sensors in the sensing system while still effectively assessing impact damage. To accomplish this goal, a stacked autoencoder algorithm is utilized to classify impact damage at different levels, meanwhile localizing the impact with high accuracy. The proposed system is validated by an impact experiment applied on a thermoplastic composite aircraft elevator in a laboratory setting. Results demonstrate the efficacy and potential of the proposed smart sensing system.

Keywords: Acoustic emission, AdaBoost, Impact damage detection, Thermoplastic composite
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1. INTRODUCTION

In-flight impact damage is one of the major threats to the structural integrity of aircraft composites. Traditional visual inspection is widely used to assess impact damage. However, it is time-consuming and prone to human error. Due to the development in sensing technique and data processing approach recently, a structural health monitoring system can now be employed to localize the impact and assess the damage automatically. This can be done either in addition to or as a partial replacement for visual inspection.

Acoustic emission (AE) is a structural health monitoring method that is extremely sensitive to damage propagation in materials [1-4]. The application of AE monitoring for fiber composite material has been explored by previous studies [for example, 5-8]. Eaton et al. [5] investigated the characterization of damage in composite materials using AE. An approach for damage characterization by measuring the amplitude ratio (MAR) of the two primary Lamb wave modes has been developed. Shahri et al. [6] worked on the damage evaluation of composite materials using AE. The authors proposed a method based on the Hilbert transform to correlate AE signals to their corresponding failure mechanisms. Dia et al. [7] utilized AE to characterize the damages in a hybrid laminate aluminum during quasi-static and fatigue tests. Principal Components Analysis (PCA), k-means unsupervised clustering analysis were utilized for the damage identification. Khamedi et al. [8] identified failure mechanisms of unidirectional carbon/epoxy composites by studying the wavelet packet transform of AE signal processing. The AE signals were converted to wavelet and then comparing with the Scanning electron microscope (SEM) observations. The results indicated that the wavelet transformed from the AE waveform could link to the damage mechanisms of unidirectional carbon/epoxy composites.

AE has also been investigated for the monitoring of the impact on fiber composite materials [for example, 9-10]. Mal et al. [9] utilized AE to detect low-velocity impacts on graphite-epoxy composite plates. The response of the plate was approached through a modified lamination theory to obtain detailed information on the relationship between the impact load and the signals. The results indicated that the occurrence of an impact loading can be easily detected from AE signals and delamination damage can be determined by analyzing the waveforms of the recorded AE signals. Saeedifar et al. [10] utilized several AE sensors to monitor the impact damage in carbon epoxy laminates under quasi-static indentation and low-velocity impact. They indicated that AE is an efficacious technique for detecting the barely visible impact damage (BVID) in composite materials.

The aforementioned studies have proven that AE monitoring of the impact on fiber composite materials is promising. However, the challenge of this approach to be applied on aircraft is to deploy a minimal number of AE sensors on the aircraft due to the environmental restriction during the operation of aircraft, while still effectively evaluate the impact damage. Machine learning algorithms, therefore, could be alternative methods to solve the problem. Artificial neural networks (ANN) and random forests have been utilized to localize the impact events with a minimal number of AE sensors [11-12]. In previous works, Soltangharaei et al. [11] proposed a system to locate impacts on aircraft components using one AE sensor. AE features were utilized as inputs to the ANN and source localization results were obtained as outputs. The results demonstrated that the impact localization using AE and ANN can provide reasonable localization results while satisfying weight and power restrictions. Ai et al. [12] further investigated the single sensor impact localization on aircraft components by employing a random forest algorithm. Results indicating random forest could achieve a better localization than ANN. However, these works only focused on impact localization, while the identification of impact damage was not investigated.

In this paper, the impact damage identification was explored. A larger number of AE signals was recorded by applying the impacts with two different levels of energy. The decision tree and AdaBoost algorithms were implemented for impact energy identification and impact localization.

2. METHODOLOGY

In this paper, an impact assessment approach for aircraft composite components was proposed. AE technique was leveraged to monitor the impact events. The impact damage level on panels was identified by decision three. The localization of impact was considered as a classification problem. The impacts will be localized to their corresponding zone. The four zones definition is presented in Figure 4.

2.1 Acoustic Emission

Acoustic emission is a physical phenomenon, which is related to the stress wave generated by the rapid release of elastic energy when cracks or damages form in materials. AE signals can be detected and collected by deploying AE sensors on the surface of an object. The method of recording and processing AE signals to diagnose the health status of an object is referred to as AE monitoring. By processing the AE signal, different AE features can be extracted. Schematic representations of commonly used AE features such as “Amplitude”, “Counts”, “Counts to peak”, “Rise time” and “Duration” is shown in Figure 1.

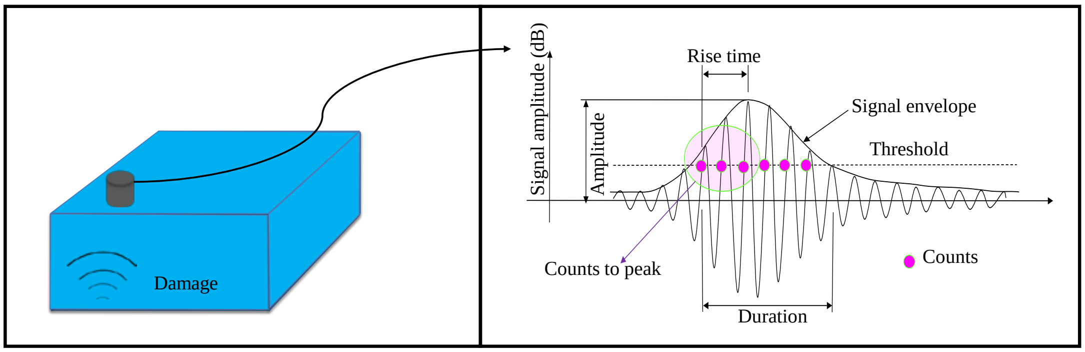


Figure 1. Schematic of acoustic emission approach

2.2 Decision tree and AdaBoost algorithm

The Boosting algorithm is an assemble learning technique that can enhance several weak learning models with a prediction accuracy that is only slightly higher than the random guess to a strong model with high prediction accuracy [13]. In cases where it is very difficult to directly construct a strong learning model, this technique provides an effective method for the design of learning algorithms. AdaBoost one of the most popular boosting algorithm. In AdaBoost, the subsequent weak learners are updated by weight in favor of the information provided by previous learners. At the end of the iterations, a strong learning model is generated [14].

The decision tree was employed as a weak model in the AdaBoost localization approach that applied in this paper. A decision tree can be constructed based on the classification threshold of each feature in the input data. At each node of the tree, the leaf node of the next layer is branched through a criterion according to the performance of the features. With layer-by-layer branching, the sample categories included in the leaf nodes will gradually become consistent, and the terminal leaf node is the classification result of the decision trees [15]. In AdaBoost, the decision tree with the lowest error is selected as the optimized tree that is implemented in the AdaBoost mode. The procedural flow of the AdaBoost model utilized in this paper is shown in Figure 2. AE parametric features are extracted from the AE signals and implemented as input. The final localization result is given by the model after the iterations of M decision trees.

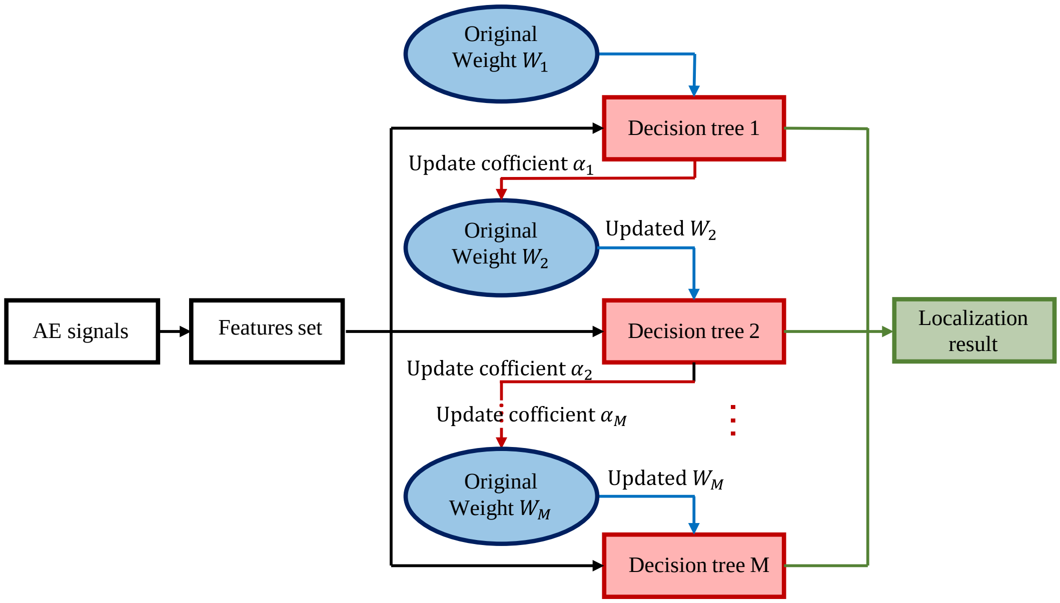


Figure 2. The mechanism of the AdaBoost model

3. EXPERIMENTATION

In this paper, a real-size elevator specimen was employed for the impact experiment. The dimension of the specimen is presented in Figure 4. The panels of the thermoplastic elevator are fabricated by a composite polymer made from two different materials: 5-H carbon polyphenylene sulfide (PPS) fabric and plain weave carbon PPS fabric. In the impact experiment, the elevator specimen was mounted on a steel test frame which is shown in Figure 3a. To simulate different impact damage levels that the elevator suffered during the flight, two steel spheres with different diameters (0.006 meters and 0.013 meters) were utilized to impact the elevator specimen. The drop height was kept constantly at 0.61 meters. A guide tube was employed to control the impact locations and the dropping height of each impact. The impact energy from two steel spheres is 0.006 J and 0.05 J. They were defined as impact level-I and level-II in this paper. The procedure of the steel sphere impact experiment is presented in Figure 3b. The impact location on each panel is presented in Figure 4 as a redpoint. Each location was impacted 60 times by the steel spheres. The dropping if the steel spheres were conducted from the left to the right of the elevator specimen. The impact experiment was monitored by a single AE sensor attached to the front spar of the elevator.

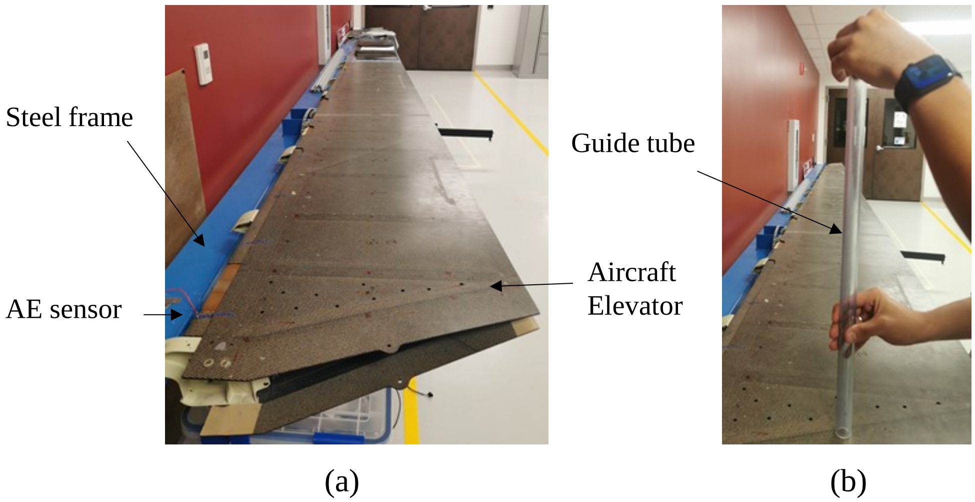


Figure 3. Steel sphere impact test: (a) Test frame setup; (b) Steel sphere impact procedure

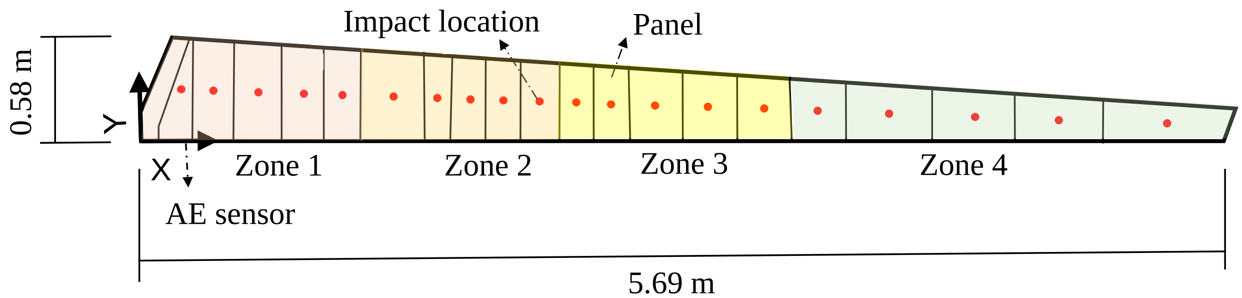


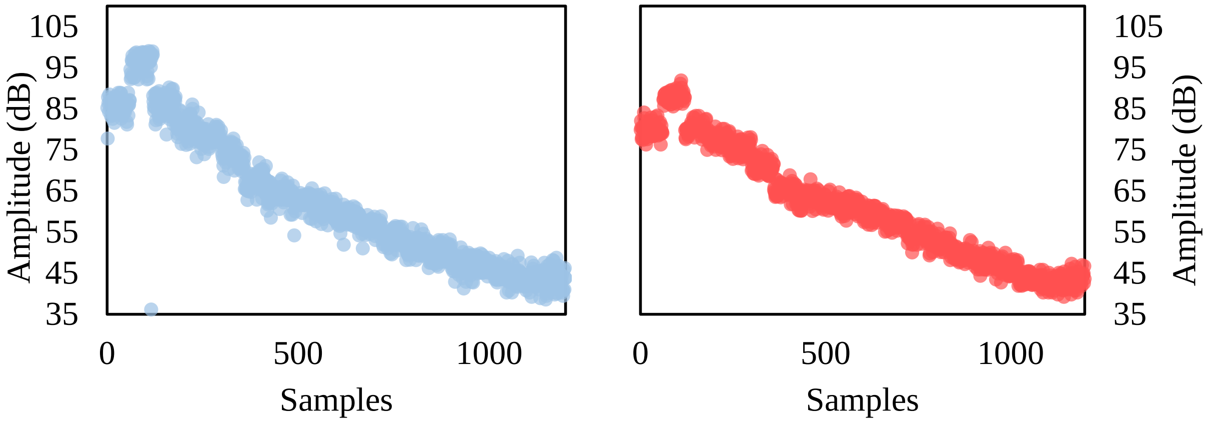
Figure 4. Impact and sensor locations

4. RESULTS

4.1 Data preparation

The data preparation was conducted for the AE signals recorded during the impact experiment. 23 parametric features were extracted from the signals and formed a feature dataset. They are “Amplitude”, “Duration”, “Rise time”, “Counts to peak”, “Counts”, “Rise angle”, “Decay angle”, “Energy”, “Absolute energy”, “Signal strength”, “Average frequency”, “Initiation frequency”, “Reverberation frequency”, “Zero crossing”, “Zero crossing frequency”, “FFT max amplitude”, “FFT width with 10% max amplitude”, “FFT width with 30% max amplitude”, “FFT crossing at 30% max amplitude”, “frequency centroid”, “Peak frequency”, “Peak power”, and “RA value”.

One of the features: the amplitudes of AE signals of level-I and II are presented in Figure 5. It can be observed that the amplitudes decreased with the increase of the distance from the AE sensor to impact location (from sample 1 to 1200). The decay in amplitude was induced by the AE wave disperse and attenuation. The amplitude of impact level-II is slightly higher than level-I because the energy release by the impact level-II more significant than the impact level-II. While they have a similar decreasing trend. The decision tree will recognize the difference between the 23 features and classify the signals into their impact levels and impact location.

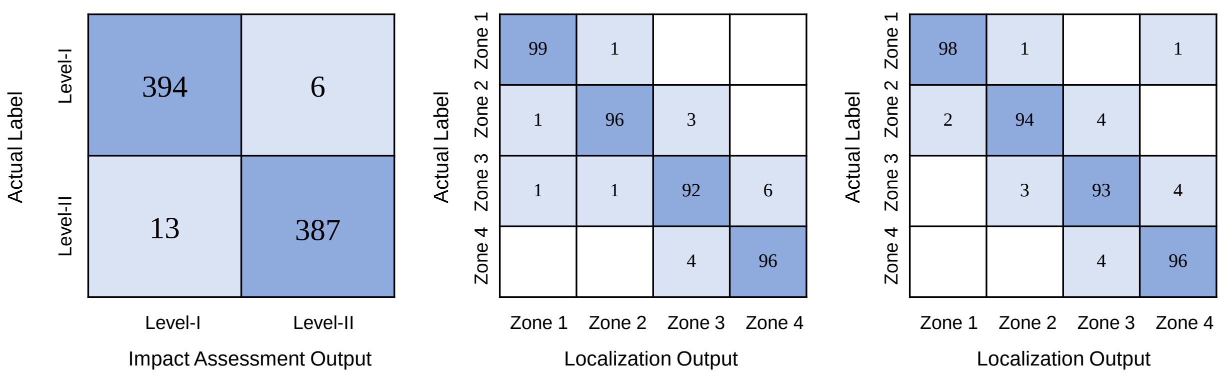


(a) (b)

Figure 5. AE signal amplitude: (a) impact level-II; (b) impact level-I

4.2 Impact level assessment

The feature dataset was forwarded to the decision tree model as input. 2/3 of data in the dataset were randomly selected and utilized as training data, the rest 1/3 were employed as testing data. The accuracy for the impact level identification is 97.6%. The results are presented in Figure 6a as a confusion matrix. 394 signals of level-I were correctly identified, 6 were identified to level-II by error. 387 signals of level-II were correctly identified, the rest 13 were identified to level-I by mistake.



(a) (b) (c)

Figure 6. Impact level identification and localization results: (a) impact level identification; (b) impact localization of impact level-I; (c) impact localization of impact level-II

4.3 Impact localization

After the impact level identification was completed, the feature dataset was then assigned to the AdaBoost model for impact localization. The training and testing ratio is the same as the decision tree. For the impacts of level-I, the accuracy of the impact localization is 95.6%. The localization results are shown in the confusion matrix (Figure 6b). Out of the 400 test signals, 383 AE signals were correctly located. In zone 1, 99 signals were correctly localized, while the remaining one signal was localized to zone 2 by mistake. In zone 2, 96 signals were successfully localized, and one was mistakenly localized to zone 1, the other 3 were located to zone 3 by error. In zone 3, 92 signals were localized to the correct zone, and one was localized to zone 1, one was located to zone 3 by error, the rest 6 were located to zone 4 by mistake. In zone 4, 96 signals were located to the right zone, the other 4 were localized to zone 3 by error.

For the impacts of level-II, the localization accuracy is 95.2%. The localization results are shown in Figure 6c. 98 signals in zone 1 were correctly localized to zone 1, one was located to zone 2, the remaining one signal was assigned to zone 4 by mistake. The number of signals in zone 2 that were successfully classified was 94, 2 were mistakenly localized to zone 1, and the rest 2 were assigned to zone 3 by error. In zone 3, 93 signals were correctly localized, and 3 were successfully localized to zone 2, the rest 4 were located to zone 4 by mistake. In zone 4, 96 signals were located correctly, the other 4 were localized to zone 3 by error.

5. CONCLUSIONS

In this paper, an impact experiment was conducted on a composite elevator specimen by using steel spheres with two different dimensions. AE monitoring was employed to collect AE signals during the experiment. A decision tree model was utilized to identify the two impact levels. An AdaBoost model was assigned to give the impact localization results.

Pertinent conclusions are:

1. By utilizing AE monitoring and a decision model, A good performance (97.6%) on the impact level identification can be observed.

2. The AdaBoost model could accomplish the impact localization with an acceptable accuracy when a single AE sensor is used. No obvious difference in localization accuracy was observed (95.6% for impact level-I and 95.2% for impact level-II) when the localization was conducted for the impacts with two different energy levels.

6. REFERENCES

[1] K. Ono. *Acoustic Emission in Materials Research-A Review*. Journal of Acoustic Emission. 1;29, 2011 Jan.
[2] K. Peters, and J. Wee. *Acoustic Modes in Optical Fibers for Lamb Wave and Acoustic Emission Detection*. Journal of Acoustic Emission.1;36, 2019 Jan.
[3] Ono K. *Review on Structural Health Evaluation with Acoustic Emission*. Applied Sciences. 8(6):958, 2018 Jun.
[4] K. Ono, Y. Mizutani, and M. Takemoto. *Analysis of Aacoustic Emission from Impact and Fracture of CFRP Laminates*. Journal of Acoustic Emission. 25(1):179-86, 2007 Jan 1.
[5] M. Eaton, M. May, C. Featherston, K. Holford, S. Hallet, and R. Pullin. *Characterization of Damage in Composite Structures using Acoustic Emission.* Journal of Physics: Conference Series, vol. 305, no. 1, p. 012086. IOP Publishing, 2011.

[6] M. Shahri, J Yousefi, M Fotouhi, and M. Najfabadi. *Damage Evaluation of Composite Materials using Acoustic Emission Features and Hilbert Transform*. Journal of Composite Materials.50(14):1897-907, 2016 Jun.

[7] Dia A, Dieng L, Gaillet L, Gning PB. *Damage Detection of a Hybrid Composite Laminate Aluminum/glass Under Quasi-static and Fatigue Loadings by Acoustic Emission Technique.* Heliyon. 1;5(3):e01414, 2019 Mar.

[8] Khamedi R, Abdi S, Ghorbani A, Ghiami A, Erden S. *Damage Characterization of Carbon/epoxy Composites using Acoustic Emission Signals Wavelet Analysis*. Composite Interfaces. 27(1):111-24,2020 Jan 2.

[9] K. Mal, F. Shih, and S. Banerjee. Acoustic emission waveforms in composite laminates under low velocity impact. *Smart Nondestructive Evaluation and Health Monitoring of Structural and Biological Systems II*. International Society for Optics and Photonics, Vol. 5047, pp, 1-122003.

[10] M. Saeedifar, A. Najafabadi, D. Zarouchas, H. Toudeshky, and M. Jalalvand. *Barely Visible Impact Damage Assessment in Laminated Composites using Acoustic Emission*. Composites Part B: Engineering, 152, 180-192, 2018.

[11] V. Soltangharaei, R. Anay, D. Begrajka, M. Bijman, M. ElBatanouny, P. Ziehl. and M. Van Tooren. *A minimally Invasive Impact Event Detection System for Aircraft Movables*. AIAA Scitech 2019 Forum (p. 1268), 2019.

[12] L. Ai, V. Soltangharaei, R. Anay, M. van Tooren, and P. Ziehl. Data-Driven Source Localization of Impact on Aircraft Control Surfaces. 2020 IEEE Aerospace Conference (pp. 1-10). IEEE, 2020

[13] G. Rätsch, T. Onoda, and R. Müller. *Soft Margins for AdaBoost*. Machine learning, 42(3), 287-320, 2021.

[14] E. Schapire. *Explaining AdaBoost*. Empirical inference, Springer. Berlin, Heidelberg, pp. 37-52, 2013.

[15] J. Myles, N. Feudale, Y. Liu, A. Woody, and D. Brown. *An Introduction to Decision Tree Modeling*. Journal of Chemometrics: A Journal of the Chemometrics Society. 18(6):275-85, 2004 Jun.