Title: *Scalable Impact Detection and Localization Using Deep Learning and Information Fusion*

Authors: Yuguang Fu
Zixin Wang
Amin Maghareh
Shirley Dyke
Mohammad Jahanshahi
Adnan Shahriar

ABSTRACT

Due to their unpredictable nature, many impact events (e.g., overheight vehicles striking on low-clearance bridges) go unnoticed or get reported hours or days later. However, they can induce structural damage or even failure. Therefore, prompt impact detection and localization strategies are essential for early warning of impact events, rapid inspection and maintenance of structures. Most existing impact detection strategies are developed for aircraft composites panels utilizing high rate synchronized measurement from densely deployed sensors. Limited efforts have been made for other applications, such as infrastructure systems or extraterrestrial human habitats, which generally require large-scale measurement and scalable detection strategies. Particularly in harsh environments, structural impact localization must be robust to limited number of sensors and multi-source errors. In this study, an effective impact localization strategy is proposed to identify impact locations using limited number of vibration measurements. Convolutional neural networks are trained for each sensor node and are fused using Bayesian theory to improve the accuracy of impact localization. Special considerations are paid to address both measurement and modeling errors. The proposed strategy is illustrated using a 1D structure, and numerically validated for a 2D dome-shaped structure. The results demonstrate that the proposed method detects and localizes impact events accurately and robustly.

INTRODUCTION

Two main types of structures are at high risk of impact events: aerospace structures and civil structures. Typical examples for aerospace structures include bird strikes on aircraft and micrometeoroid impact on spacecraft [1]. For civil structures, vehicles/ship collisions on bridges are the main threats of concern [2]. Prompt impact detection and localization strategies are of great importance for early warning of impact events and rapid maintenance of structures.

Various techniques have been developed for impact detection and localization during the past three decades. They can be classified into two categories: (1) physics-based methods relying on the laws of physics, e.g., acoustic waves propagation rate [3,4], and (2) data-driven methods using data interpretation without mechanical information, e.g., neural network [5,6]. Most strategies utilize high-rate, tightly synchronized data obtained from densely deployed sensors, e.g., aircraft panels or wings [7]. Very few efforts of impact detection/localization have been conducted to cover large areas using limited number of sensors under harsh environment, e.g., human habitats in deep space.

To address the limitations, this paper presents a novel strategy of impact localization using a limited number of sensors by applying deep learning and information fusion, i.e., effectiveness holding if only one sensor survives. The strategy is illustrated using 1D structure and further validated in a 2D dome structure, emulating the meteorite impacts in the deep space. The results demonstrate that the proposed strategy can accurately identify impact locations under sensor limitations and multi-source errors.

SCALABLE IMPACT LOCALIZATION STRATEGY

The objective of this study is to develop a robust and efficient algorithm for impact localization, while achieving graceful degradation following individual sensor failures. In addition, as part of the fault detection and diagnosis module for a smart deep space habitat simulation [8], it is also required to have acceptable computation cost for real-time execution, at a sampling rate of less than 1 kHz. The proposed method consists of two main components: convolutional neural network for impact localization for a single node and Bayesian fusion of multi-sensor measurement for higher precision, as detailed below.

CNN for impact localization

We divide the surface areas of structures into multiple zones and apply the convolutional neural networks (CNN) to classify which area is most likely subjected to impacts. Figure 1 shows the framework of proposed data-driven strategy for impact localization. After an impact happens, a certain length of time history record is collected. A CNN classifier is trained for each sensor measurement data to provide probabilities of every zone of structural surface. If we deploy N sensors, N classifiers will be obtained, sharing the same architecture but different weight value. Afterwards, we conduct information fusion after impact localization results from each classifier is obtained. This idea makes the proposed strategy robust and scalable. If some sensors are damaged after impacts, the measurement data from the survived sensors can still present acceptable results. The more sensors survive, the higher accuracy it can achieve.

The time-frequency energy distribution is leveraged here for feature extraction. In particular, we use continuous wavelet transform to get more informative features for the CNN. The wavelet transform uses windows that are longer for lower frequencies and shorter for higher frequencies. Such multi-resolution analysis of the wavelet transform provides a sharp time-frequency representation, ideal for analyzing nonstationary signals containing the information of impact occurrences. The continuous wavelet transform of a signal x(t) is expressed below,

$$W_{\psi}^{x}(a,b) = |a|^{-1/2} \int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-b}{a}\right)dt \tag{1}$$

where ψ is the wavelet function, and the analytic Morse wavelet is adopted here. The resulted signal is a 2D matrix, with the size of 61 (scale levels) × 501 (sample number), given that the signal is sampled at 1 kHz.

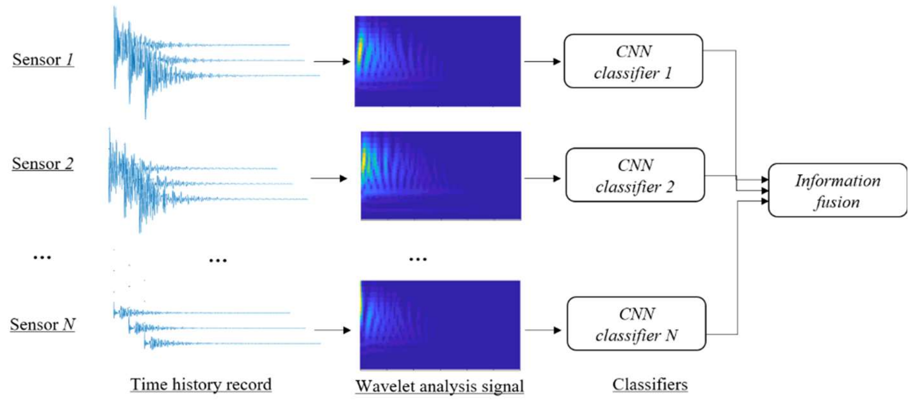

Figure 1. A scalable data-driven framework for impact localization

Figure 2 shows the architecture of the CNN for Sensor *i* for impact localization. It reads 2D image signal from wavelet transformation, and extract shift-invariant features through n feature learning layers. The feature learning layer sets include a convolution layer, a batch normalization layer, an activation layer and a max pooling layer. The required number of feature learning layer, *n*, depends on the complexity of the structure subjected to impacts, and the number of neurons in the fully connected layer, *m*, is determined by the number of zones for impact locations.

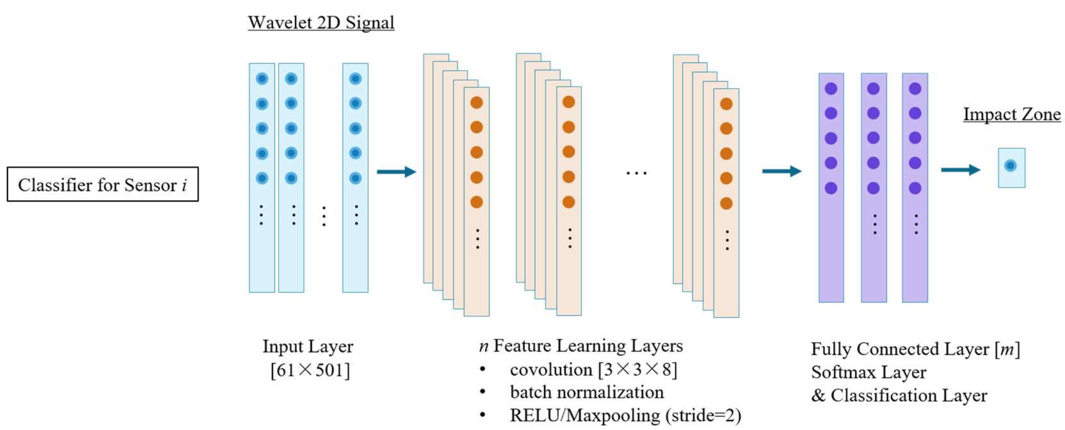

Figure 2. Architecture of a convolutional neural network for Sensor *i* for impact localization

Information fusion

The objective of information fusion is to combine the probability outputs from multiple CNN classifiers for each sensor and produce more accurate results for impact localization. To this end, Bayesian theory is adopted here. Particularly, the probability of an impact, $I_{n,s}$, is defined as below.

$$I_{n,s} = p(L = n|S_i = s) = f_i(s) \tag{2}$$

where f_i is the probability outputs from CNN classifier *i* corresponding to Sensor *I*; *n* is one of potential zones on the structural surface, and *s* is the wavelet signal observed by

Sensor *i*. Furthermore, the probability of an impact J_n inferred by *M* sensors can be expressed as below,

$$J_n = p(L = n|S = s_1, \dots s_m) = \frac{\prod_{m=1}^{M} I_{n,s}}{\sum_i \prod_{m=1}^{M} I_{i,s}} \tag{3}$$

In addition, a loss function *l* is defined to identify the most likely impact location in which the loss function is minimized. The optimal localization results, J^* is expressed below,

$$J^* = \arg\min_r \sum_n l(r,n) J_n \tag{4}$$

where *n* is the true impact location, while *r* is the searched impact location. The loss function *l* can be defined as a square matrix, where the diagonal items are all zeros, and rest of them are ones. Its dimension is $N \times N$, where *N* is the number of impact zones.

ILLUSTRATIVE EXAMPLE

This section presents numerical illustration of the proposed strategy by building a 1-dimensional (1D) model and discussing the performance of impact localization. The proposed strategy is written in MATLAB language and trained/tested using the Deep Learning toolbox.

The 1D numerical model is established to illustrate the capability of the proposed strategy, as shown in Figure 3. It is a 10 degree-of-freedom (DOF) linear system. The governing motion of equation is expressed as,

$$\boldsymbol{M}\ddot{x}(t) + \boldsymbol{C}\dot{x}(t) + \boldsymbol{K}x(t) = \boldsymbol{f}(t) \tag{5}$$

For simplicity, the mass, stiffness and damping parameters for each DOF are set to be the same. Specifically, $m_i = 29.13kg$ $k_i = 1190 \times 10^3 \mathrm{N/m}$ and modal damping ratio is considered here, with damping ratio $\xi_i = 0.0097$. Modal damping is considered.

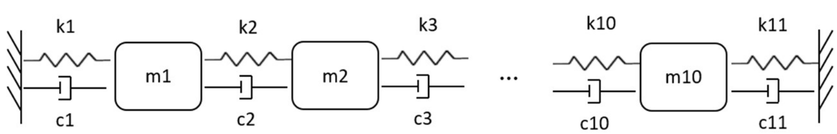

Figure 3. 1D model with 10 degree-of-freedoms

The 1D model is implemented in Simulink. The structural dynamic responses, i.e., accelerations of all DOFs, are obtained with a sampling rate of 1 kHz and a time history of 10 s. The impact force is simulated as an impulse signal, applied to any one of DOFs at 2 s, with different level of amplitude, ranging from 0.1 N to 10 N. Different level of noise floors in dBm are considered to illustrate the performance of proposed strategy in various structural operating environment. Furthermore, modelling errors are included for some simulations, to emulating the discrepancies between the ideal structural model for the CNN training and the actual physical structure with uncertainties. The definition of modelling error *Err* is defined as the summation of discrepancies for all stiffness k_i.

$$k_i^* = k_i + \Delta k_i^+; \;\; Err = \sum_i |\Delta k_i^+| = 2\%, 5\%, 10\% \dots \tag{6}$$

The obtained wavelet transform signal of raw time history data contains essential information starting from impact happens. By examining the signal plot, only 2 seconds of signal within a frequency band of 15 to 115 Hz is processed for wavelet transform to allow higher resolution of input features. The impact hits each DOF and accelerations of all 10 DOFs are collected. A total number of 1000 datasets are processed by wavelet analysis. 60% of data is the training subset, 20% is validation subset, while the rest 20% is testing subset. Three feature learning layers are adopted in the CNN architecture.

Figure 4 shows the learning curve for the sensor located on Node 10. As can be seen, both training and validation rates quickly converge to 100%. 25 iterations are sufficient to achieve the best results. The confusion matrix shows that all the impact locations are successfully identified with no errors. The same behavior is found for the sensors located in other nodes. Therefore, there is no need to do information fusion. This is because the structure is relatively simple to construct the relationship between the impact location and the measurement data. Additional tests also show that the effect of measurement and modeling errors are negligible for the structure.

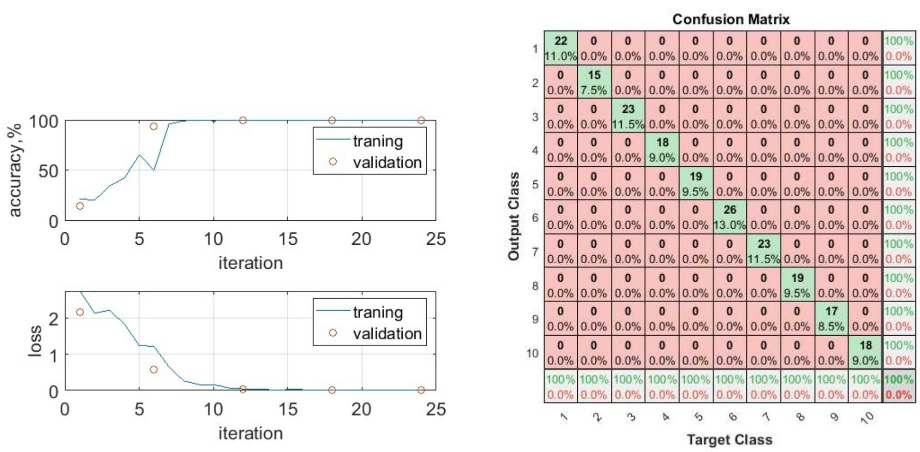

Figure 4. Impact localization for 1D structure: (a) learning curve, and (b) confusion matrix

In real applications, the structural system has high stiffness (e.g., dome-like structure in most deep space habitat design) but limited sampling rate for measurement. In this case, the collected measurement data can only cover very limited frequency band of interest and hence limited useful information. Such situation eventually increases difficulty to successful impact localization. Therefore, the stiffness of the 1D structure is increased, by multiplying the k_i with a factor of 350. As a result, its natural frequencies are increased. If the sampling rate is kept the same as 1 kHz, the effective frequency band can only cover first three natural frequencies. Meanwhile, the signal decays in a much quicker way than the previous case. The same process and setup are repeated for a stiff 1D structure, and the information fusion are applied to the classification results from each node. Without loss of generality, we choose the sensor on the 1st node as a single sensor to detect impact location, and then gradually add more sensors to conduct information fusion for impact localization. As can be seen in Figure 5, when the noise energy increases, the accuracy of impact localization for the same sensor setup decreases, but information fusion helps to maintain the high accuracy by adding more sensors, mitigating the adverse impact of noise errors. Likewise, when the modelling error increases, the accuracy of impact localization for each node is reduced significantly. The information fusion helps to mitigate the adverse impact of modelling error, but not quite a lot. In any case, the proposed solution works as long as one sensor is survived during the impact event.

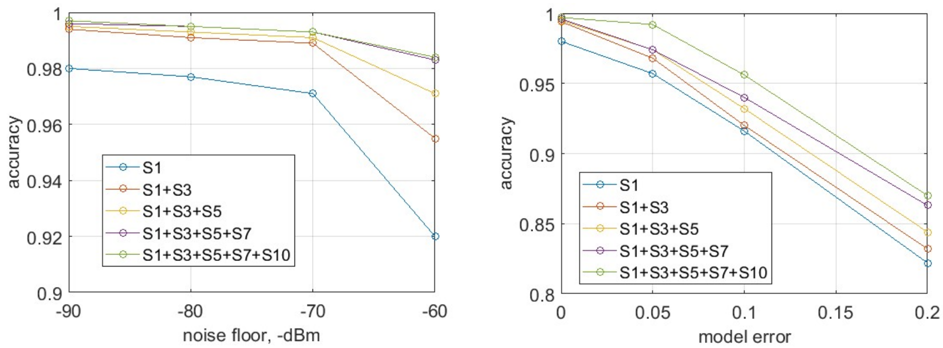

Figure 5. Impact localization for 1D stiff structure: (a) accuracy for measurement errors, (b) accuracy for modelling errors.

2D DOME STRUTURE EVALUTATION

To further evaluate the proposed strategy, a 2D dome structure representing a deep space habitat structure is built and simulated under meteorite impacts. The model is built for a monolithic spherical dome, emulating the habitat dome illustrated by ESA (Figure 6). It has an inner radius of 2.5 m, an outer radius of 2.9 m, and a 0.4 m-thick circular foundation, coded in MATLAB. It is assumed to be made of regolith concrete material, supporting both static and dynamic nonlinear analysis. The material was assumed to enter a damage state when the hoop stress exceeded the tensile or compressive yield strength of the material.

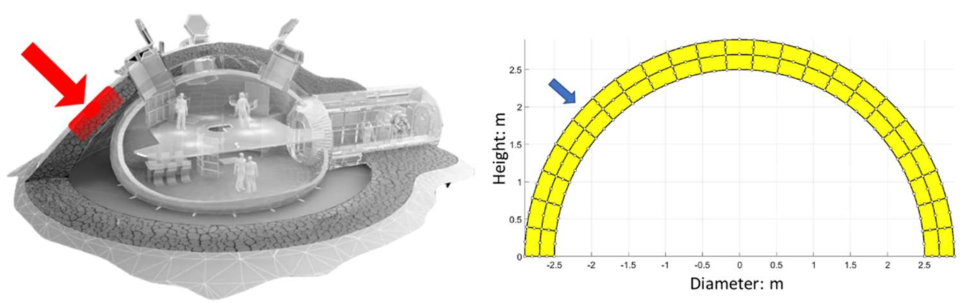

Figure 6. Deep space habitat simulation under meteorite impacts: (a) habitat sketch (credit: ESA) (b) 2D simplified model.

The 2D dome structure is divided into 11 segments for impact localization, as shown in Figure 7. Each segments have four nodes on the outer surface of meshed finite element model, except the segment in the middle with five nodes. In addition, a total number of 9 sensors are deployment on both outer and inner surface. They are uniaxial, along with the radial direction, as illustrated in the figure. The impact loads are applied at each node on the outer surface with the magnitude ranging from 0.1N to 10N. As a result, a total number of 45 × 100 loading cases are executed, and some of them resulted in nonlinear behavior of the 2D model, indicating potential damage. During each loading case, uniaxial acceleration for each sensor is collected at a sampling rate of 1 kHz. The simulation shows that, the 2D structure has high stiffness; the vibration decays quickly within 0.5 second. Therefore, only 0.5s measurement data is collected for each loading case. In addition, to accommodate the difficulties of impact localization, the same CNN architecture is applied, but using 12 feature learning layers. The learning parameters are kept the same for 1D illustrative example.

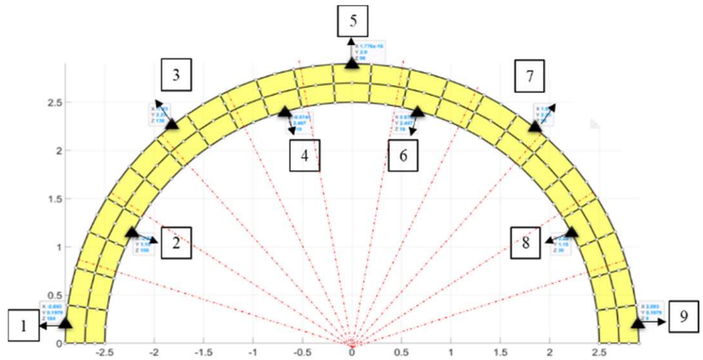

Figure 7. Impact localization setup: 11 division for localization and 9 uniaxial sensor deployment.

A total number of 9 CNN classifiers are obtained for impact localization. As shown in Figure 8, a distribution of accuracy for each classifier is obtained. The first observation is that the middle sensor classifier can only achieve around 50% at maximum. This is because the symmetric of dome structure making the classifier confused, especially for the sensor in the middle. The minimal noise floor is considered as -144 dBm, corresponding to the sensor specification in the lab, and three additional level of noise floors are included for the test. As can be seen in the figure, the accuracy is reduced as the noise floor increases. Such analysis can also help to identify the best setup of sensor deployment for impact localization. In the follow-up study of information fusion, we intentionally exclude Sensor 5, for the sake of generality. It can be found that information fusion can help to mitigate the adverse effect of measurement errors.

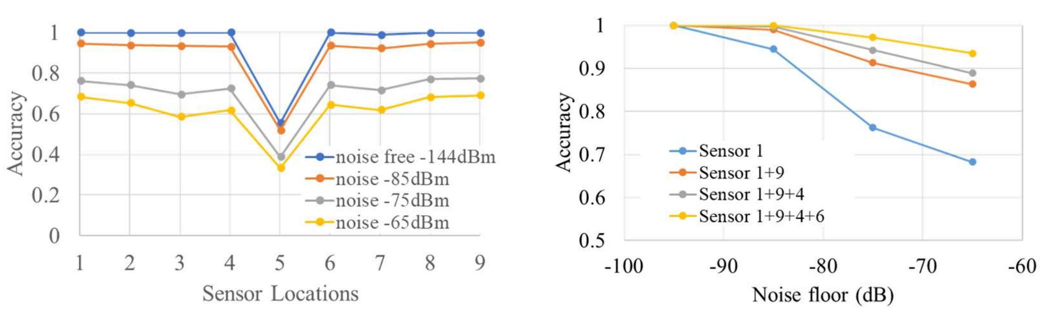

Figure 8. Impact localization results: (a) single sensor CNN result, (b) information future results.

CONCLUSION

This paper presents a novel strategy for impact localization using deep learning and information fusion. It is robust and scalable, suitable for harsh environment (e.g., deep space habitat) where sensors may damage under impact events. In particular, deep learning classifier for each sensor is trained, and information fusion is applied to improve the accuracy of localization. Such design can help to mitigate the adverse effect of measurement errors and modeling errors, which are common and critical challenges for similar studies. The strategy has been illustrated using 1D structure model and further been evaluated for 2D dome structure for a deep space habitat.

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REFERENCES

1. Polimeno, U., and Meo, M. (2009). "Detecting Barely Visible Impact Damage Detection on Aircraft Composites Structures," *Composite Structures*, 91(4): 398-402.
2. Garner, A. C., and Huff, W. K. (1997). "The Wreck of Amtrak's Sunset Limited: News Coverage of a Mass Transport Disaster". *Disasters*, *21*(1): 4-19.
3. Kundu, T. (2014). "Acoustic Source Localization," *Ultrasonics*, 54(1): 25-38.
4. Jang, B. W., and Kim, C. G. (2021). "Acoustic Emission Source Localization in Composite Stiffened Plate Using Triangulation Method with Signal Magnitudes and Arrival Times," *Advanced Composite Materials*, 30(2): 149-163.
5. Morse, L., Khodaei, Z. S., and Aliabadi, M. H. (2018). "Reliability Based Impact Localization in Composite Panels Using Bayesian Updating and the Kalman Filter," *Mechanical Systems and Signal Processing*, 99, 107-128.
6. Tabian, I., Fu, H., and Sharif Khodaei, Z. (2019). "A Convolutional Neural Network for Impact Detection and Characterization of Complex Composite Structures," *Sensors*, 19(22): 4933.
7. Shrestha, P., Kim, J. H., Park, Y., and Kim, C. G. (2015). "Impact Localization on Composite Wing Using 1D Array Fbg Sensor and RMS/correlation Based Reference Database Algorithm," *Composite Structures*, 125, 159-169.
8. Dyke, S. J., Marais, K., Bilionis, I., Werfel, J., & Malla, R. (2021, March). "Strategies for the Design and Operation of Resilient Extraterrestrial Habitats," In *Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2021*. International Society for Optics and Photonics.