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CHARACTERIZATION OF MICROMETEOROID AND ORBITAL DEBRIS IMPACTS ON SPACE STRUCTURES USING DEEP LEARNING NEURAL NETWORKS INCORPORATING EXPERIMENTAL AND SIMULATED DATA

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ABSTRACT

Deep Learning Neural Network (DLNN) algorithms are introduced in this work to detect the occurrence of MMOD impacts, determine the location of the impact site, and classify the severity of consequent damage. To address the challenges of limited empirical training data and ensuring robustness to varying test conditions, training DLNN is explored using a mixture of simulated and experimental data. Even with a relatively small training data set, the effectiveness of this approach was demonstrated for characterizing low velocity impacts on representative Whipple shielding structures.

Keywords: acoustic emission, deep learning neural network, numerical models, impact characterization

NOMENCLATURE

AE	acoustic emission
DLNN	deep learning neural network
MMOD	micrometeoroid and orbital debris
NDE	nondestructive evaluation

1. INTRODUCTION

Micrometeoroid and Orbital Debris (MMOD) impacts on spacecraft and large space structures are a significant hazard that can compromise mission success and endanger the lives of crew [1]. Acoustic emission (AE) signals and impact shocks generated by MMOD impacts can be detected by an array of inexpensive, replaceable, wireless surface sensor units affixed to the external surfaces of the spacecraft or space structure [2-3]. Through accurate estimation of the severity of damage, appropriate maintenance actions can be performed. However, the interpretation of AE signals can be complex. Determining impact location and the severity of consequent damage is also complicated by variations in structure geometry, sensor location, and sensor operational state.

Deep Learning Neural Network (DLNN) algorithms are introduced in this work to detect the occurrence of MMOD impacts, determine the location of the impact site, and classify the severity of consequent damage. Specific challenges exist with transitioning emerging DLNN algorithms directly for nondestructive evaluation (NDE) applications. Prior successful NDE applications of neural networks have been dependent on taking care to reduce the dimensionality of the data and provide reliable features as inputs for classification [4-5]. Alternatively, training deep learning neural networks requires very large, well-understood data sets. Relative to many problem spaces like image, voice, and text recognition, NDE is considered 'data starved'. To address the challenges of limited empirical training data and ensuring robustness to varying test conditions, a novel design approach for training DLNN algorithms is proposed for impact damage classification. The classifier is split into three sub-classifiers that address (1) damage detection (2) damage localization and (3) damage severity. To address the need for a very large training data set, a hybrid approach is introduced that incorporates a mixture of experimental and model-generated data.

2. MATERIALS AND METHODS

2.1 Experimental and Simulated Studies

An impact generation apparatus and acquisition software were constructed to collect experimental impact event data from multiple sensors along with relevant metadata. For the single sensor study, a small 24” x 24” representative Whipple shield served as the acoustic medium. Using steel spheres with diameters of 0.125”, 0.25” and 0.5”, five drop heights, and 24 impact locations, 3,600 waveforms were captured. For the multi-sensor study, a large 36” x 48” representative Whipple shield was used as the acoustic medium. Using steel spheres with diameters of 0.25” and 0.5”, 24 impact locations, and three drop heights, a total of 1,440 waveforms were captured.

Initial simulated studies using FEM (COMSOL) were performed to demonstrate agreement with experimental AE tests, and begin to investigate the use of simulated data in DLNN training. Simulated results for a pencil-lead break were first considered at 5 locations. These few simulated results were enhanced by a factor of 1000x by varying the calibration level of the sensor (over 10 levels) and adding more than 100 randomized samples of noise.

2.2 Time-Frequency Signal Pre-processing

During this ball drop study, the signal from the single sensor was split into two channels to capture different features of the waveform. The first channel was used to acquire a high gain sample of the early transient response while a second low gain channel (2) was also acquired to measure the full magnitude of the transient response of the impact. The high gain channel provides improved signal to noise of the early transient signals, for example the S0 mode features. While these high frequency components are lacking in channel 2, this low gain measurement does avoid serious truncation artifacts found in the high gain spectrogram. An option considered in this study was the mixing of features from the high gain and low gain spectrogram. Figure 1 shows how the left portion of the high gain spectrogram and the right portion of the low gain spectrogram can be mixed to provide an improved feature map of both the S0 and A0 response for classification purposes. These 2D spectrograms were used as inputs to the DLNN based classifiers.

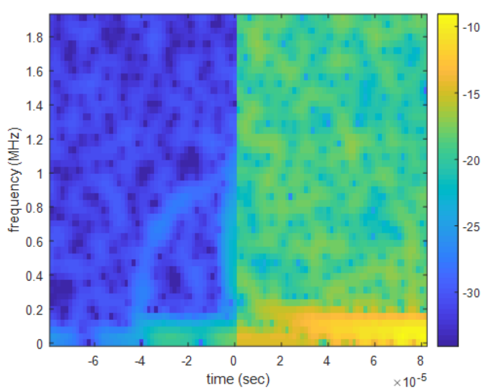

FIGURE 1: EXAMPLE OF MIXED TWO CHANNEL SPECTROGRAM FOR A 0.5" DIA. STEEL BALL DROP FROM 50 cm, DISTANCE FROM SENSOR = 31 cm.

3. RESULTS AND DISCUSSION

An initial classification problem was to estimate the distance from an impact event to a single transducer. The DLNN design incorporated an initial convolution neural network, several small hidden layers, and final regression layer, trained to output an estimate of the distance between the impact and transducer. Training was performed using 67% of the sample set. Results are present in Figure 20 [left] using a remaining subset (33%) of the original data points [valid. set 1] and a collection of hybrid data samples at three independent locations [valid. set 2]. For the pencil-lead break shown in Figure 2(a), there was good agreement between the known and estimated values, for both validation test sets. Results are presented in Figure 2(b) showing localization of the ball drop test. Results were generally good, but more spread was observed in the results relative to the simulated pencil-lead break results. This error trend is likely associated with some variability in the drop location and the lack of an S0 mode feature in the measured ball drop data, which is helpful for distance classification. A few outliers were noted, but these were discovered during post-analysis to be a result of an ambient 'noise' trigger event.

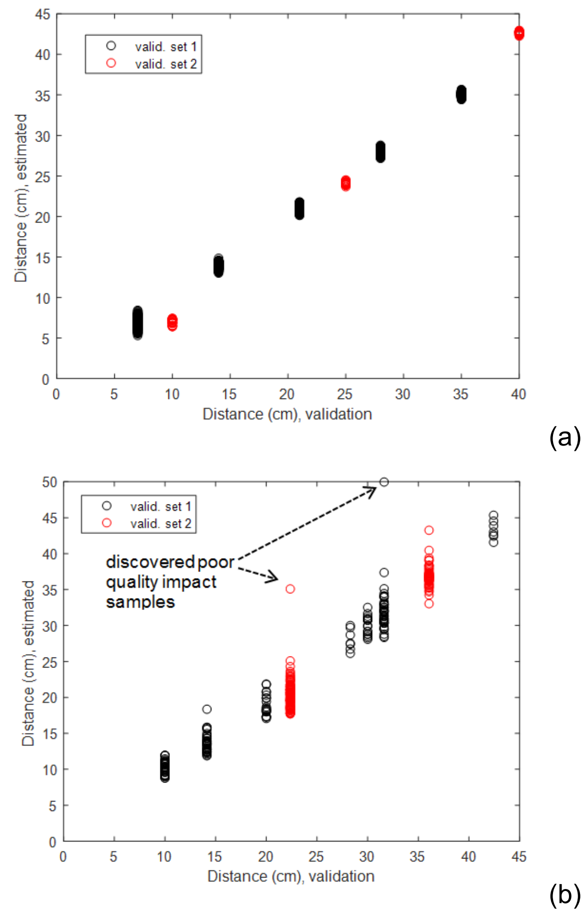

FIGURE 2: DLNN RESULTS FOR IMPACT DISTANCE LOCALIZATION (a) USING HYBRID SIMULATED DATA SET WITH NOISE ENHANCEMENT, AND (b) AN EXPERIMENTAL DATA SET WITH VARYING DROP DISTANCES AND HEIGHTS.

4. CONCLUSION

Deep Learning Neural Network (DLNN) algorithms are introduced in this work to detect the occurrence of MMOD impacts, determine the location of the impact site, and classify the severity of consequent damage. A series of DLNN classifier demonstrations were achieved addressing damage detection, 1D and 2D localization, and impact energy. Even with a relatively small training data set, the effectiveness of this approach was demonstrated for characterizing low velocity impacts on representative Whipple shielding structures. Through these studies, insight was also gained into ways to improve the sensing scheme, signal processing and DLNN algorithm design for improved classifier performance for future efforts.

ACKNOWLEDGEMENTS

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