Recurrent Neural Networks for Identification of Acoustic Wave Reflections

Mulugeta Haile!, Christopher Hsu, Natasha Bradley, and John Chen

U.S. Army Research Laboratory
Aberdeen Proving Ground, Maryland

Abstract
We consider the problem of identifying boundary reflections of an acoustic emission (AE) wave in geometrically complex structures during structural health monitoring (SHM). The goal is to exclude the reflections during severity and location analyses. We perform supervised learning to identify reflection markers on a time series data. We propose, long short-term memory recurrent neural network (LSTM-RNN), to learn a distinct manifold of the direct AE wave and its dispersion characteristics in a given material. The manifold will be accompanied by a likelihood scoring scheme based on the mapping from wave space to a latent space. Applied to a new AE data, LSTM-RNN, labels reflected waves based on their fit into the learned distribution. Results on acoustic emission test on an isotropic plate demonstrate that the approach correctly identifies reflections of the direct wave.

1 Introduction
Acoustic emission (AE) is the transient elastic wave created when there is a rapid release of energy in a material. It happens during plastic deformation, phase transformation or material fracture. For over a decade, AE has been successfully used to passively sense the initiation and progress of material damage in geometrically simple structures, such as pressure vessels and 2D plates. However, AE as a SHM technique has yet to find success in health monitoring of geometrically complex and interconnected structures such as a full-scale air-frame \(1\)\(^{-3}\). There are two primary reasons: (1) in complex structures the AE wave travels at various velocities while undergoing multiple boundary reflections before being received at a surface mounted transducer. In many occasions the direct wave and its reflections are indistinguishable and hence cause erroneous source localization; (2) in interconnected dynamic structures, most of the AE hits come from non-damage related events such as the clicking sound of fasteners, rubbing of panels, and vibration. These hits are quite similar to damage related AE waves both in statistics and frequency. Conventional signal processing techniques using traditional AE signal statistics, such as rise-time, duration, signal energy or transform domain characteristics such as wavelet parameters, peak amplitude, etc, do not work in addressing either of the above two issues. This paper is concerned with the first issue, i.e. the identification of AE wave reflections \(4\)\(^{-6}\).

In the sequel, recurrent neural networks (RNN) are used to learn distinct patterns of the direct and reflected AE waves in much higher dimensions. RNNs

----------------------------------
*mulugeta.a.haile.civ@mail.mil
are well suited to recognize patterns in time series data such as the type generated by AE sensors. Long Short-Term Memory (LSTM) is the building block for layers of RNN. LSTM was first introduced by Hochreiter and Schmidhuber (1997) (7) to deal with the exploding and vanishing gradient problems when training traditional RNNs. Relative insensitivity to gap length (8) gives an advantage to LSTM over alternative RNNs or hidden Markov models and other sequence learning methods in various applications. Recent development in LSTM include introduction of forget gates (11) and peep-hole connections (9). The LSTM model used in this paper uses forget gates for sequence classification.

2 Training Data

The training data is collected using the test setup shown in Figure 1. Two broadband AE sensors (Model KRNm300) are attached to each side of the grooved aluminum plate. The sensors are electrodeless nickel plated brass construction with an electrically isolating ceramic face. They have an excellent sensitivity in 200-850 kHz range. AE time series data is acquired and stored using a high speed acquisition board (Model AMSY-6). The acquisition threshold is set at 40dB, sampling rate is 5MHz, and the pre- and post- trigger pointes are set at 200 samples. The grooved aluminum plate, shown in Figure 1, is designed in such a way that each Hsu-Nielson event (pencil break) will produce a direct wave for one sensor and a reflection the other sensor, depending on the relative location of the sensor and event around the groove. For example, if a pencil is broken at one of the locations close sensor 2, it will be receive as a direct wave at sensor 2 while sensor 1 will receive a reflection wave as there is no linear direct path for the wave to travel. This test setup creates an equal number of direct and reflection waves that can then be used for training and testing. As stated, the artificial AE generation follows the standard Hsu-Nielson practice, where a 0.5 mm lead pencil with a rubber guard is held at a 45-degree angle and broken. Pencil breaks are conducted at the cross location shown in the figure. Each test experiment includes 21 breaks which produce 42 samples of direct and indirect waves. Additional test data is also obtained with random breaks closer to the boundaries of the test plate. Examples of direct and reflected AE wave data are shown in Figures 2 and 3.

Figure 1: Acoustic emission data was collected using Hsu-Nielson sources at various locations. The test specimen is a grooved Aluminum plate. Two acoustic emission transducers, Sensor 1 and Sensor 2 are attached at locations shown.
3 Data Pre-Processing

As stated earlier, we are looking to correctly identify whether a recorded acoustic wave is direct wave (direct line of sight between source and channel) or reflected wave. Being able to accurately distinguish the two can have significant benefit on the accuracy of future AE-based structural damage detection and localization. The classification of the acoustic emission wave is characterized as a binary output, with 0 for direct and 1 for reflection. Labeled data is collected as described in section 2 with each pencil break producing a direct wave at one channel location and reflections at the other channel location. In order for the data to be processed in the LSTM network, it needs to go through some preprocessing steps. Since LSTMs are made for long term dependencies, computational memory usage may increase significantly for long (length) time-series datasets. Due to the format of data collection in the test, some samples have a length of 64,000 data points which is an vary large for our purpose. To process this many data points as features for each sample in a classical neural network, it would take heavy computing power which is just not feasible (especially for on-board applications). In general, it is beneficial to resize the data by removing points that does not add value in the training of the network. Hence, the pre–processing involves removing pre– and post–trigger data points as well as extended prolonged data near acquisition threshold. This improves the computational efficiency and accuracy of the network. By limiting the data to what is being identified, the network is much less likely to over fit or even skip over the essential attributes.

For each experiment (42 signal samples), each sample is shortened by down–sampling signal to 2.5MHz (from the original 5MHz). Hence, the data is windowed to 2000 data points which include 100 pre-trigger points. An example of the original data and the truncated data for both the direct and reflected waves are shown in Figures 2 and 3.

![Figure 2: Representative unfiltered time-series data of the direct wave from Sensor 1, (a) Full-length data, (b) Widowed data.](image)

4 Results and Discussions

All datasets are concatenated together and then split up and randomized with 80% of the data used for training and validation while the remaining 20% is used for testing. The network parameters are adjusted to best suit this dataset. Two stacked LSTM layers are used with 64 hidden nodes in each layer and the training was run for 256 epochs. The $\ell_2$ regularization term is used to avoid exploding gradients and the Adam optimizer is used to combat the noise problem, which is common in sensor data. We also use a batch size of 64, a learning rate of $\alpha = 0.0015$ and loss $\lambda = 0.0015$ for the $\ell_2$ term to train the system. When training is initiated, the data is quickly evaluated to check if
Figure 3: Representative unfiltered time-series data of the reflected wave from Sensor 1, (a) Full-length data, (b) Widowed data.

it has been properly normalized. When that is confirmed, the training begins. Throughout the training procedure, at every epoch, the model is evaluated by the training set and is also tested against the test set. Accuracies and batch losses are calculated for training and is shown in Figure 4. When all the training is complete and the model is compared to the test set followed by calculation of performance metrics. Performance metrics used in this test are precision, recall, and $F_1$ score.

Figure 4: Training losses and accuracies over training iterations for acoustic emission data obtained using two broadband sensors on a 2D plate.

Figure 5 shows normalized confusion matrix showing the classification performance of the network implemented here. It can be seen that LSTM RNNs can successfully classify direct and reflection acoustic emission waves. Here the LSTM was able to classify a test set with an accuracy over 90%. However, there is still room for the model to be improved. While those figures are great for this specific situation, the test data still come from data collected in a lab where most factors can be controlled, i.e. such as constant temperature, minimal ambient noise, and relatively simple structural geometries. Our dataset is also quite small compared to datasets found in other deep learning applications such as vision and speech recognition. Those datasets have millions of variations that can give the classifier a chance to learn every possible scenarios. The reason to mention this is to emphasize the importance of generalization and the problem of overfitting. The LSTM networks goal is to optimize its weights and biases based on the loss from the training set. It can be seen in the training log that over several epochs, training accuracies increase for the test set and slowly reach a perfect accuracy of 100%. However, this success can negatively affect the test
accuracy due to overfitting.

Overfitting is a common problem in deep learning applications. If trained too specifically for a given training set, the model will not generalize well to new data. There are a few techniques in order to generalize a model which include more training samples of different scenarios, use of dropout and randomization at each epoch. In the future, we will look to create more data with different scenarios such as performing pencil break at non-centered locations on the test specimen. This process could diversify the training data by varying timing and reflection angles. Different sizes and shapes of aluminum plates can also be used with additional nuts and bolts put in place in order to simulate a more realistic airframe structure. Besides combatting overfitting through increased data size and diversity, the implementation of dropout and randomization at epochs can be used. Dropout is the technique of randomly ignoring certain nodes in the network in order to create some disorder in the data. Training has been seen to create dependencies amongst normally connected nodes and but once in a while ignoring a few based on a certain probability, we can hope to dissuade the creation of these dependencies which produce an overfitting model. Finally, we can also look to randomize the data at every epoch. In this paper, the data is randomized at the very beginning but from there on out it stays in that order. Similar to the idea of dropout, the specific order can create some overfit features between samples of the data. Through the use of randomization at every epoch, the network will be fed a new combination of these same samples to ensure there is no correlation in the order.

5 Conclusions

In sum, this project has shown that LSTM RNNs can be successfully used to improve the performance of acoustic emission based structural health monitoring by accurately classifying direct and reflected waves in geometrically complex structures. This paper is a summary of an attempt to automatically discern the difference between a direct wave and a reflection wave. While our LSTM produces promising results, this is only the first step in building a full diagnostic system. The purpose for using deep learning techniques is to be able to use raw data. The fact that it was necessary to preprocess the data is not ideal for real world application. Although it seems clear that only the first portions of the data samples are important for classification, it is hard to fully discount that maybe the rest of the data is necessary. Also, the need for the preprocessing shows an inefficiency from data collection to classification. In future projects,
we will focus on the elimination of the preprocessing step. Finally, we will look to implement other techniques in order to generalize our model. Overfitting is a common problem in deep learning and it is necessary to take measures to prevent it. The robustness of our model can be further improved by generating diverse set of training data that mimics all possible scenarios of AE sources, reflection interfaces, material conditions as well as test environment.

References


