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DEEP NEURAL NETWORK-BASED GUIDED WAVE DAMAGE LOCALIZATION

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ABSTRACT

Damage detection and localization remain challenging research areas in structural health monitoring. Guided wave-based methods that utilize signal processing tools (e.g., matched field processing and delay-and-sum localization) have enjoyed success in damage detection. To locate damage, such techniques rely on a model of wave propagation through materials. Measured data is then compared with these models to determine the origin of a wave. As a result, the analytical model and actual data may have a mismatch due to environmental variations or a lack of knowledge about the material. Deep neural networks are a class of machine learning algorithms that learn a non-linear functional mapping. The paper presents a deep neural network-based approach to damage localization. We use simulated data to assess the performance of localization frameworks under varying levels of noise and other uncertainty in our ultrasonic signals.

Keywords: Structural health monitoring, damage localization, matched field processing, deep neural network.

NOMENCLATURE

SHM	Structural Health Monitoring
MFP	Matched Field Processing
ML	Machine Learning
ANN	Artificial Neural Network
RF	Random Forest
DNN	Deep Neural Network

1. INTRODUCTION

Damage detection and localization is a central theme in the non-destructive evaluation and monitoring methods to assess the fidelity of structures. To remotely detect and locate damage, guided waves-based systems have been implemented for a number of structures. Data obtained from such systems is highly dispersive and complex owing to the interaction of waves with the complex propagation media.

Damage localization in a complex medium can be seen as a source localization problem. Multiple methods have been proposed in signal processing literature for the same. These include array processing and beamforming methodologies [1]. In guided waves literature, these concepts are often realized as delay-and-sum algorithms [2]. A generalization of delay-and-sum, known as matched field processing (MFP), is also extensively used in radar and underwater acoustics [1].

MFP is a model-based framework. It compares a known model with experimental data to find the location of maximum correlation between model and data. The localization performance of MFP is limited by the ability of the analytical model to capture the variability due to environmental conditions and the complexity due to the dispersive nature of waves.

Damage localization can also be set up as a problem of learning a non-linear mapping from wave data to a target location in the propagation media. This is similar to multilateration approaches based on time of arrival measurements [3].

Neural networks, a class of machine learning technique, has seen a recent resurgence in popularity. Recently, neural network-based methods have been able to improve underwater acoustics source localization [4].

We briefly discuss the theory behind MFP and its challenges in Section 2. In Section 3, we introduce neural networks followed by our proposed deep neural network-based framework for damage localization that is robust under noisy and uncertain conditions. In Section 4, we outline our experiments and results. In Section 5, we conclude our work.

2. MATCHED FIELD PROCESSING

A matched field processor compares a mathematical model for wave propagation against experimental data at every target location in the grid. The target point giving maximum correlation with the data is the predicted location of the source or damage. The ability to build a model makes the MFP approach flexible. As guided waves are dispersive, the ability of MFP to deal with

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broadband signals makes the approach more suitable for SHM applications than traditional delay-and-sum localization [5].

Consider a grid of dimensions $L \times W$ populated with sensors and damage at some location. The damage is considered as a scatterer. Sensors placed on the grid act as transmitters or receivers. Consider we have M sensor pairs. The experimental data is a $Q \times M$ matrix across Q frequencies and M measurements. We denote the data as $X(\omega_q, r_m)$ for frequency 'q' and measurement from sensor pair m. Let $\bar{Z}(\omega_q\ , r_m)$ be our analytical model. A signal b_p is calculated for every point 'p' in our grid such that

$$b_p = \frac{\left| \sum_{m=1}^{M} \sum_{q=1}^{Q} X(\omega_q\ , r_m)\, \bar{Z}^*(\omega_q, r_m, p)\ \right|^2}{\sum_{m=1}^{M} \sum_{q=1}^{Q} |\ \bar{Z}(\omega_q, r_m, p)|^2} \tag{1}$$

where $(.)^*$ represents the complex conjugate. The estimated location from the processor is given by the maxima of Eq. 1 over all of the points.

MFP is likely to suffer from model mismatch due to environmental variations. Researchers have proposed methods to create data-driven models from baseline guided wave data using sparse signal processing methods [6]. MFP performance is further limited by the robustness of each matched field processor to environmental variations and uncertainties. This leads us to explore novel localization techniques that can achieve greater robustness to experimental variations.

3. MACHINE LEARNING

A central theme of machine learning algorithms is to learn a mapping from input to output using functional transformations. ML algorithms have been successfully applied to a variety of problems ranging from image recognition [7] to underwater acoustic source localization [4].

3.1 Deep neural network-based framework

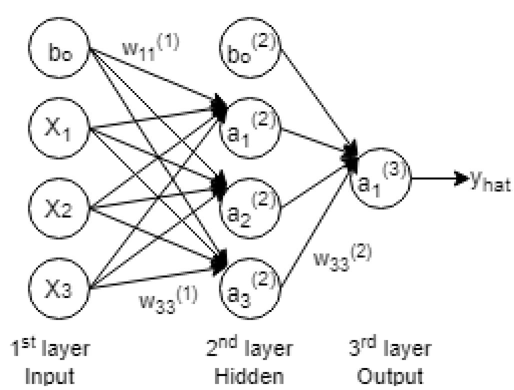

FIGURE 1: NEURAL NETWORK WITH ONE HIDDEN LAYER

Artificial neural networks consist of hidden layer(s) with nodes. The interconnections between subsequent hidden layers have unique, trainable parameters known as weights. Every node sums up the incoming signals and applies an activation function to get the output. This signal is passed on to subsequent hidden layers and ultimately to the output layer. At the output layer, a suitable loss function is optimized to make the predicted output go as close as possible to the actual output. The optimization process updates the trainable parameters (weights) of the neural network. An illustration of ANN is shown in Fig 1.

Deep neural networks are neural networks with multiple hidden layers. DNN's can learn complex non-linear functions due to multiple hidden layers. DNN's also provide the advantage of directly feeding input data to the model with the need for less feature engineering (input transformation). This sets apart DNN's from other ML techniques [8].

To train our network, we simulate a Q (time samples) $\times$ M (sensor pair measurements) matrix of the wave data. We refer to this matrix as one "sample" in our dataset. We flatten the sample ($Q \times M$ matrix) into a 1D vector to be fed as input to the DNN. Our DNN framework has 2 hidden layers. The 1st hidden layer has $n_1 = 500$ nodes and second hidden layer has $n_2 = 60$ nodes. At the output, we have 2 nodes, one each for the horizontal and vertical grid location. Loss function at the output is the mean squared error between the DNN prediction and the target output. We then test our network with additional simulation data with previously untrained parameters and compare the results.

4. VALIDATION SIMULATION

We assume an $L \times W$ grid. We simulate damage as a point non-uniformity at a random location which leads to the scattering of waves. The simulated waves are measured at various locations by randomly placed point sensors. Each sensor can act as a transmitter or receiver. We do not incorporate reflection at structure boundaries in this initial research. With this assumption, we generate simulated data using the general solution to the wave equation. Later, we add white Gaussian noise to our signal to simulate noisy conditions.

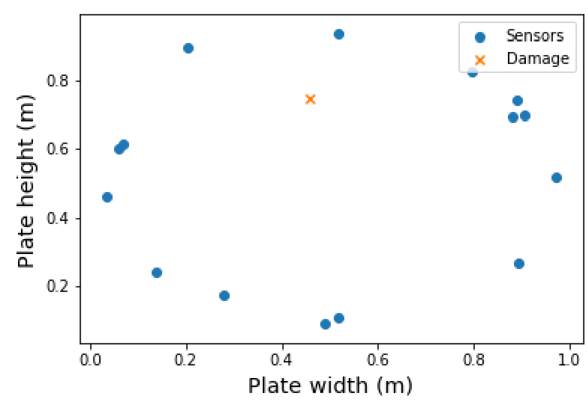

FIGURE 2: DAMAGE LOCALIZATION SIMULATION SETUP

An illustrative simulation setup is shown in Fig 2. Simulation data is generated for $Q = 500$ frequencies in the range of 0 to 1000 KHz. We simulate m = 15 sensors at random locations thereby giving M = 210 sensor pair measurements. While the optimum placement of sensor arrays is a widely studied research problem [9], the focus of our research is to demonstrate the usability of DNN in the context of damage localization. Hence, we use a random placement of sensors.

We perform t = *2000* Monte Carlo simulations for wave data, thereby giving t = 2000 samples to separately train and test our DNN. Recall that each sample is $Q \times M$ matrix. In every simulation, a random location is chosen for damage. The measurement of simulated wave data at sensor locations is the input to the DNN framework and the random damage location is the output from DNN. The hyperparameters of the DNN as discussed in Section 3.1, are critical to the performance of the DNN [10]. We experiment with multiple parameter values to find an optimal structure. To assess the DNN, we use a localization error performance metric defined by

$$\text{error} = \frac{1}{\text{T}}\sum_{t=1}^{T} |\text{ target location} - \text{predicted location}| \qquad (2)$$

where T is the total number of samples in the dataset.

We add noise of varying levels to test the robustness of different localization frameworks. Signal to noise ratio is defined by

$$\text{SNR}_{\text{dB}} = 10\log_{10}\left(\frac{\text{SIGNAL}}{\text{NOISE}}\right) \qquad (3)$$

where SIGNAL is signal power and NOISE is noise power.

For completeness, we compare our DNN framework with another supervised ML technique known as random forests. RF is a statistical supervised ML technique that provides competitive performance on a variety of supervised learning problems [11]. RF consists of multiple predictors, each of which learns rules to map input to output from training data.

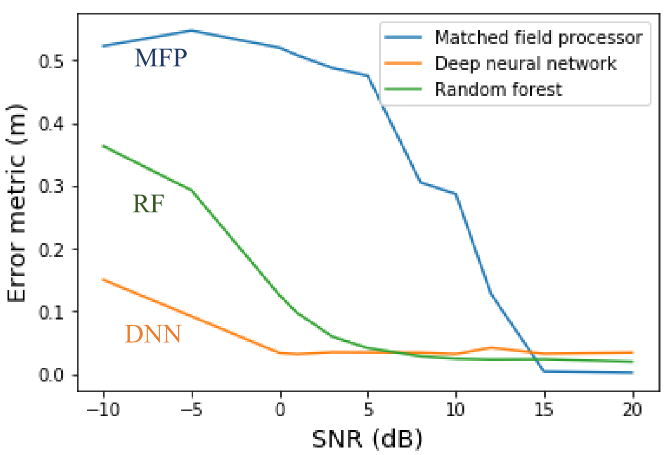

FIGURE 3: ERROR AT VARYING NOISE LEVELS

Fig 3 shows the performance of three methods: matched field processing, deep neural networks, and random forest. We observe that our DNN based framework performs better than the other two methods for high noise levels (low SNR) while MFP is better at low noise levels (high SNR).

5. CONCLUSION

We proposed a deep neural network based-framework for damage localization in structures. Using simulated data, we compared our framework with the traditional matched field processing technique. The performance of MFP was observed to be slightly better than DNN for high signal-to-noise ratios but DNN significantly outperformed MFP when the signal-to-noise ratio was low. The results show a huge promise from DNN's for damage characterization in SHM.

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