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A New Classifier Network for Ultrasonic NDE Applications based on Ensemble Deep Learning

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***Abstract*— This work presents a classifier architecture for Non-Destructive Evaluation (NDE) applications which can robustly detect the presence and location of flaws using an ensemble of deep learning networks. The ensemble draws upon the effective sequential time analysis of Long Short-Term Memory - Neural Networks (LSTM–NN), the function estimation and prediction properties of Wavelet Neural Networks (WNN), and the feature extraction capabilities of Convolution Neural Networks (CNN). Simulation results confirm that the proposed architecture offers highly reliable flaw detection and localization with significant Flaw to Clutter Ratio (FCR) enhancements.**

***Key Words*—Neural Networks, Deep Learning, LSTM, WNN, CNN, NDE, ANC, Flaw Detection**

I. Introduction

Neural networks have been applied to NDE applications for flaw detection in the presence of noise [1]. This work looks to extend upon this previous work and explore the feasibility of an ensemble of neural networks as a flaw detector. The ensemble of neural networks consists of outputs from LSTM-NN [2], WNN [3], and CNN [4] combined into a fully connected neural network.

LSTM-NN introduce the ability to add memory to a neural network. Hence, LSTM-NN is a popular choice for language translation and modeling, speech recognition, image captioning, and financial analysis. CNN has excellent data feature extraction capabilities. This makes it a popular choice for image recognition, detection, and analysis, as in the case of medical imaging. WNN has detailed function estimation properties. This makes it suitable for classification, prediction analysis techniques, and noise reduction.

Ultrasonic imaging of materials to detect flaws can be corrupted by the presence of random interference and attenuation. This is due to the properties of the material and size of the material grains [5]. Comparing the ultrasonic frequency wavelength to the size of the grains, this is generally considered Raleigh scattering. A flaw is usually larger than a grain, so the flaw acts as a reflector. In order to enhance the flaw signal from the noise, a generic technique without any scattering characteristics of the material known a priori would be beneficial. This paper investigates an Adaptive Noise Cancellation (ANC) technique based upon LSTM-NN which could be used without any prior knowledge of the medium. This LSTM-NN ANC would be the first stage input to the ensemble neural network to enhance the signal from the noise.

II. Ensemble Based Ultrasonic Flaw Detection

The overall system architecture proposed in this work is depicted in Fig. 1. Ultrasonic A-scans are the input data to the system. The A-scans are scaled from 1 to -1 first, before the neural network evaluation for input data consistency.

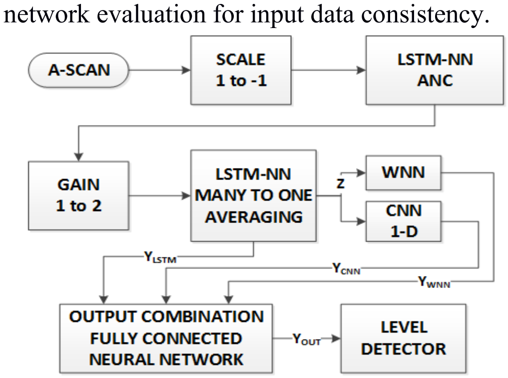

Fig 1. System Level Block Diagram

A. LSTM-NN ANC Architecture

ANC is a technique of estimating a signal corrupted by noise or interference. Its advantage lies in the fact that no prior knowledge of the signal or noise is needed [6]. In the classical sense, ANC has been implemented using adaptive filtering such as Least Mean Squares (LMS). ANC would nominally be implemented with an input signal, and a reference signal, as a two-input system. However, in the case when the signal is narrowband and the noise is broadband, or vice versa, a delayed version of the input signal can be used as the reference signal. A diagram comparison of the adaptive filter ANC compared to a LSTM-NN ANC is show in Fig 2. For the LSTM-NN ANC, this would be for the learning phase (back propagation) of the algorithm. For the test implementation, a delay of 8 samples was used.

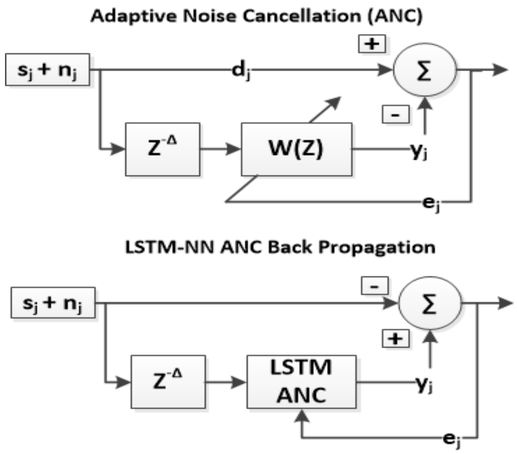

Fig 2. ANC System Level Block Diagram Comparison

The LSTM-NN ANC uses a prediction method to create the output. The LSTM-NN ANC architecture, as an example of 3 predictions, is depicted in Fig 3. For the test implementation, the number of predictions was 4, the number of layer depths was 2, and there was 45 LSTM cells/block.

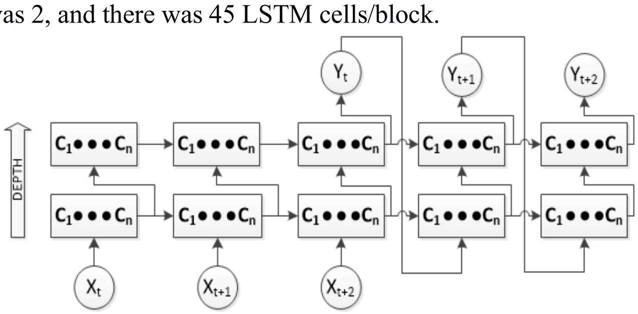

Fig 3. LSTM-NN ANC Implementation

B. LSTM-NN Many-To-One Architecture

The LSTM-NN Many-To-One will take "n" number of sequential data points and is trained to output the desired average of these values. Due to this effect, the LSTM-NN will down sample the original A-scan data length. The LSTM-NN Many-To-One architecture is depicted in Fig 4. For the test implementation, the number of samples averaged was between 4 and 8 depending upon the A-scan length, the number of layer depths was 2, and there were 50 LSTM cells/block. From the figure, the outputs Z_t to Z_{t+n} are inputs to WNN and CNN.

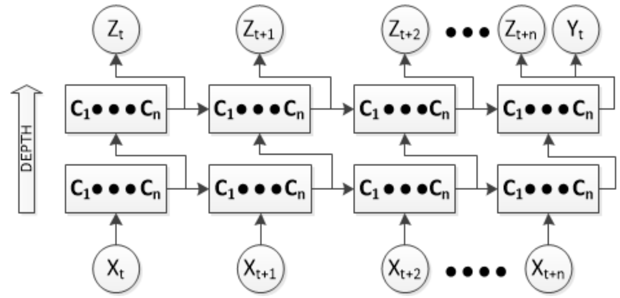

Fig 4. LSTM-NN Many-To-One Implementation

C. CNN Architecture

The CNN is a one-dimensional convolution process. The input data to the CNN are the outputs Z_t to Z_{t+n} from the LSTM-NN Many-To-One. There can be any number of convolutions processes to extract features from the data. Pooling on the output of the convolution can be used to simplify the number of calculations. The CNN architecture, as an example for 3 features, is shown in Fig 5. For the test implementation, the number of convolution nodes was 100, the number of features was 3, and pooling was 1. Just like in the case of the LSTM-NN Many-To-One, the CNN output data is down sampled from the original A-scan data length.

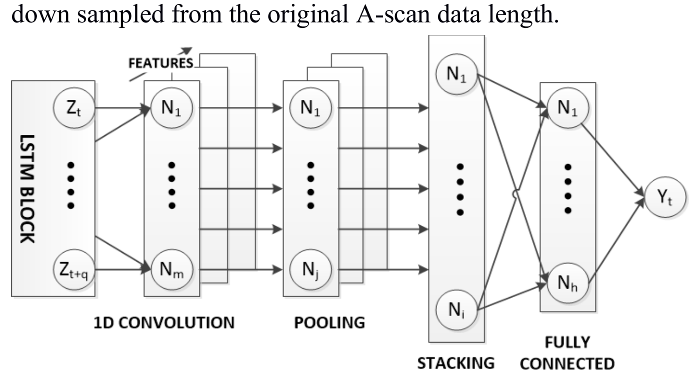

Fig 5. CNN Implementation

D. WNN Architecture

The WNN uses wavelet functions as the node activation. The learned parameters in the wavelet functions are the translation and dilation wavelet parameters. The wavelet family could be, as examples, Morlet or Ricker. The input data to the WNN setup are the outputs Z_t to Z_{t+n} from the LSTM-NN Many-To-One. The WNN architecture is shown in Fig. 6. For the test implementation, the number of wavelet nodes was 1024, and the Ricker wavelet was used. Just like in the case of the LSTM-NN Many-To-One, the WNN output data is down sampled from the original A-scan data length.

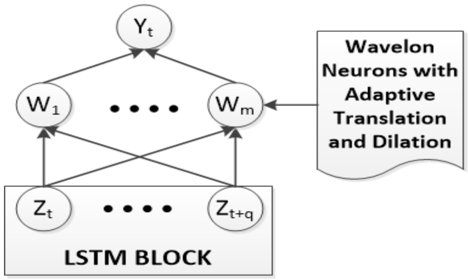

Fig 6. WNN Implementation

E. Output/Level Detection Architecture

The final network in the sequence combines the outputs from the LSTM-NN Many-To-One, WNN, and CNN. This is a fully connected multiple layer combinational neural network.

The level detector can be set to an arbitrary level that would determine if a flaw exists or does not exist. The level detector is the last stage after the output network layer. For the test implementation, the level detector was set to 0.5. Above 0.5 there was a flaw, and below 0.5 there was no flaw.

III. Data Sets

Two types of A-Scan data sets were evaluated. There was simulated data and experimental real data sets.

A. A-Scan Simulated Data Set

The simulated A-scan input data was simulated using ultrasonic measurement system models [7]. Each data set length was 1024 samples. The A-scan data input to the system consisted of training data and evaluation data. There were 50 A-scans of each type listed in Table I.

Table I. Simulated Data Set Summary

	Flat Bottom Hole with System Noise	Side Drilled Hole with System Noise	Crack with System Noise	System Noise Only
Training	X	X	X	
Evaluation	X	X	X	X

B. A-Scan Experimental Real Data Set

Experimental ultrasonic data were acquired from Panametric A3062, which is a broadband ultrasonic transducer of 0.375 diameter with 5 MHz central. A steel block of type 1018 and grain size 50µm was used. Each data set length was 2048 samples. The A-scan data input to the system consisted of training data and evaluation data. There were 14 A-scans of each type listed in Table II.

Table II. Experimental Real Data Set Summary

	Flaw with System Noise	System Noise Only
Training	X	
Evaluation	X	X

IV. Table III. Evaluation Data Summary of Results

Flat Bottom Hole	Side Drilled Hole	Crack	System Noise Only Simulated Data	Flaw Real Data	System Noise Only Real Data
(1)	(1)	(1)	(2)	(1)	(2)

Note (1): *All flaws detected. No false targets.*

Note (2): *No false targets.*

V. Results

MATLAB was used to generate the results. Figures 7 – 8 are LSTM-NN ANC sample outputs for simulated and experimental real data when a flaw is present. Figures 9 -12 are ensemble sample outputs for simulated and experimental real data, and when a flaw is present and is not present. Table III is a summary of results.

A. LSTM-NN ANC Simulated and Experimental Real Outputs

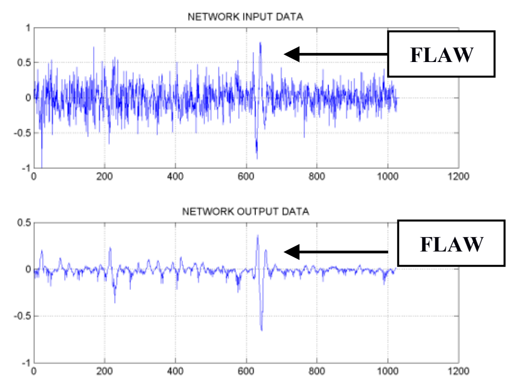

Fig 7. LSTM-NN ANC single flaw in A-Scan Simulated Data

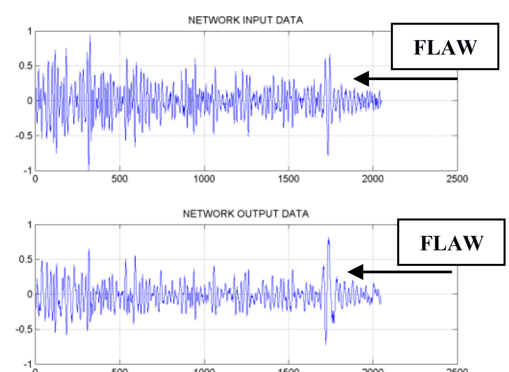

Fig 8. LSTM-NN ANC single flaw in A-Scan Experimental Real Data

B. Ensemble Simulated and Experimental Real Outputs

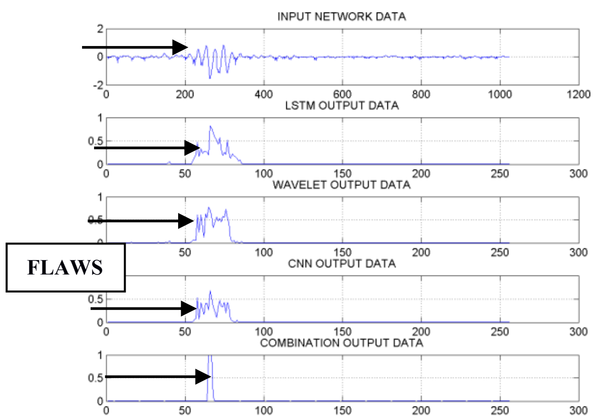

Fig 9. Ensemble crack flaw in A-Scan Simulated Data

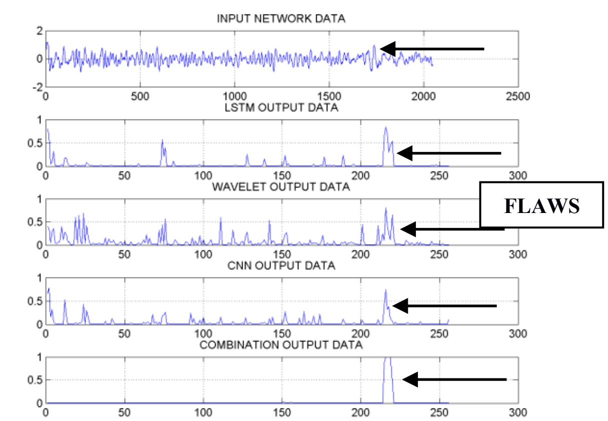

Fig 10. Ensemble single flaw in A-Scan Experimental Real Data

C. Ensemble "No Flaw" – Simulated/Experimental Outputs

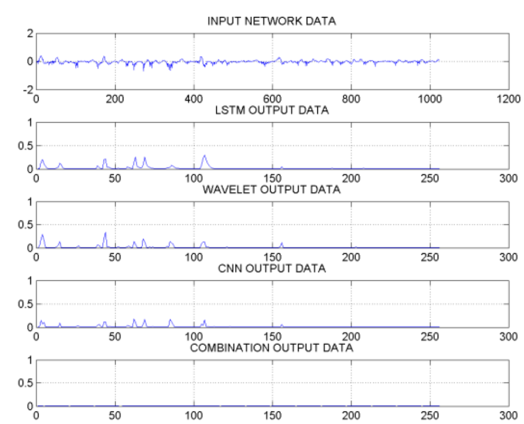

Fig 11. Ensemble – No flaws present A-Scan Simulated Data

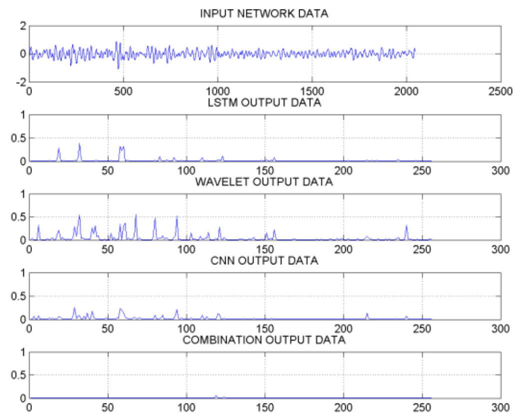

Fig 12. Ensemble – No flaws present A-Scan Experimental Real Data

VI. CONCLUSION

This work presented an ensemble of neural networks for NDE. With preliminary results using simulated and experimental data, 100% accuracy was shown to be able to identify when a flaw existed, or did not exist, and the location of the flaw in the sequence. The proposed system could enhance the FCR by up to 30db.

Further work in this project would be to test this architecture in different NDE environments, and with different types of flaws/background noise and validate the accuracy performance.

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