Ultrasonic Flaw Detection based on Temporal and Spectral Signals Applied to Neural Network

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***Abstract*— Ultrasonic Non-Destructive Evaluation (NDE) uses high frequency acoustic waves to evaluate materials, and often signal processing is required to detect echoes from defects in the presence of micro-structure scattering noise. Scattering noise is known as the clutter. The clutter interferes with the flaw signal and cannot be completely separated from it by using conventional signal processing methods such as subband filtering. In this paper, a Neural Network (NN) is used for ultrasonic flaw echo detection using two different methods to design and train the networks. The first method is based on pattern recognition in time domain. The second algorithm is a combination of the Split Spectrum Processing (SSP) and NN. Eight frequency components are extracted from the original signal to train the NN. Both algorithms have reliable accuracy for target echo detection. The feasibility of using machine learning algorithms for material characterization and signal analysis is also discussed.**

Keywords*— *Target Detection, Neural Network, Split Spectrum Processing

I. Introduction

Ultrasonic Non-Destructive Evaluation (NDE) has been applied widely in industrial and medical applications. Signals acquired from the ultrasonic NDE are often noisy due to the scattering effect by the microstructure of the test object. Inside the material, ultrasonic signal experiences reflection, refraction and mode conversion [1]. The received signal is a superposition of multiple ultrasonic signals scattered from the original ultrasonic interrogating wavelet. The noisy channel makes ultrasonic signal processing difficult by conventional techniques [2] [3]. The target echo recognition method should reveal the hidden information such as the defect signature in the test subject. Since there could be different types of target echoes with different characteristics, the target detection algorithm should be adaptive to physical conditions of test objects. This paper adopts a machine learning algorithm to achieve ultrasonic target echo detections.

A major task in training a neural network is to find the proper training data set. To collect sufficient inputs for training the NN in this study, a steel specimen with a defect is tested. The position of the transducer, and the location of the defect within the material is already known in the test setup. With this arrangement, the position of the defect in the captured signal can be identified. Two different training methods are applied for the flaw detection. The first algorithm segments the input in the time domain, the segmented signal is used as the training input. The second algorithm is Split Spectrum Processing (SSP) to sub band the signal in 8 frequency bands. These frequency bands form an 8-dimensional training input for the NN. To explore NN based algorithms, the Embedded Projector is used to project high dimension data into a 3-dimentional space. This projection shows that both algorithms can separate the defect signal from the micro-structuring scattering clutter signal.

The A-scan [4] shown in Figure 1a is acquired using a 0.5-inch diameter broadband ultrasonic transducer of with 5 MHz center frequency. The data is sampled at the rate of 100 MSPS (Million Samples Per Second), with 8-bit resolution. In the experiment, a steel block with several defects (holes of 1.5 mm diameter) is used as the target of interest within the specimen. Figure 1b is the power spectrum of the A-scan, the frequency of the signal ranges from 1.5 MHz to 9 MHz. Multiple A-scans are required for training and validating the design of neural network.

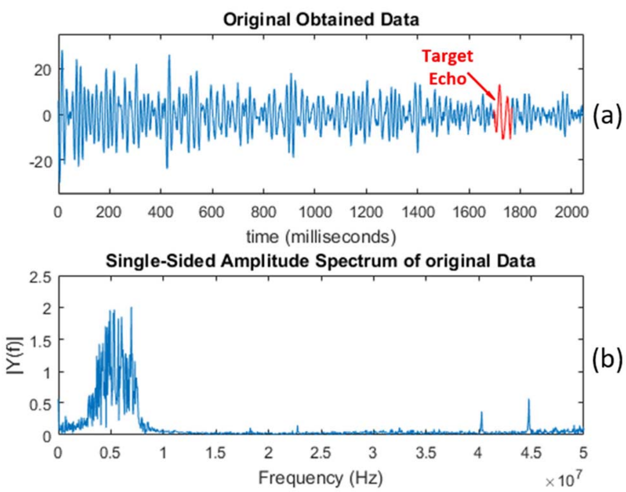

Figure 1. (a) Original A-scan with Target Echo; (b) Power Spectrum of the Original A-scan

II. Target Detection using NN Pattern Recogonition

Since we are training the NN to recognize the target echo with a specific pattern, it is intuitive to use a segment of an A-Scan in the time domain to train the NN. Based on the experiment, we know that most of the target useful information is concentrated in the frequency band from 1.5 MHz to 6 MHz. To prepare the data for training the A-Scans are passed into an FIR filter to remove the unwanted frequency component. After

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the FIR filter, the signal is normalized. The most important task is to recognize the pattern of the target signal. Normalizing the input will reduce the impact of the absolute amplitude of the training signals. Then, the signal will be separated into frames to generate training data set. Figure 2 shows how the frames are generated. Each frame contains 50 samples. The length of each frame is decided by the duration of the ultrasonic target signal. Each frame has overlap with other frames. To get a better training of the NN, the overlap should be as large as possible. An output array will be generated corresponding to the training input. The output array uses a '1' to indicate the target detected and a '0' for the non-target.

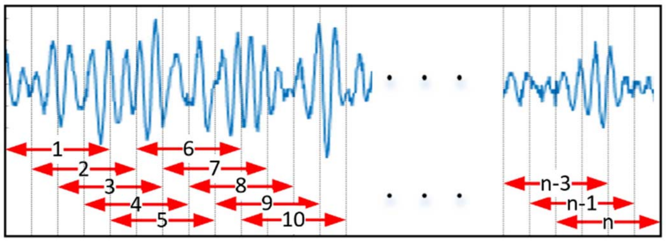

Figure 2. Data Segmentation for Neural Network Training

The input array obtained from the segmentation has a dimension of 50. TensorFlow, an open source software library for numerical computation using data flow graphs, has a tool called the Embedding Projector [5] which allow users to project high dimension data into 2D or 3D space. This is an intuitive way to understand the data we use to train the NN. A method called Principal Component Analysis (PCA) is used to compute the top 10 principal components of the 50-dimension input array. We have chosen three components from these ten as the basis of the new embedding projection in 3D space. Figure 3a and 3b are two different view angles of the same embedding projection; target echoes are marked as solid bigger dots in red in the figure and non-target echoes are smaller dots in gray. Embedding projection graph clearly shows that it is possible to train a NN to separate target from non-target echo.

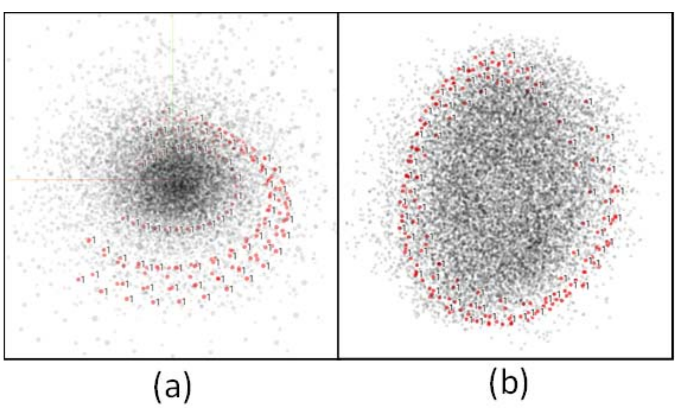

Figure 3. Training Data Plotted in Embedding Projector of TensorFlow

Figure 4 shows the NN structure of the ultrasonic target detection based on the pattern recognition. This NN has 4 layers: an input layer with 50 nodes, an output layer with 1 node, a first hidden layer with 40 nodes and a second hidden layer with 30 nodes. This training is only based on the shape of the input signal in the time domain. Multi-hidden layer and more nodes in each layer will improve the precision of the training result.

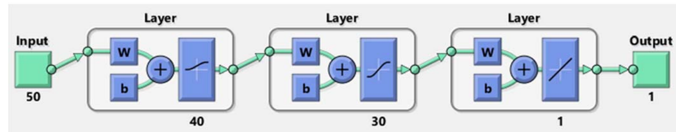

Figure 4. Neural Network Structure

A back-propagation algorithm is used to train the NN. When training starts, all NN nodes are initialized with random coefficients. It takes many iterations to train the neural network. After each iteration, a training dataset is fed into the NN to calculate a predicted result with current coefficients. A cost function represents the distance between predicted result and the actual result. The purpose of the training procedure is to minimize the cost function. By using the predicted results, an error term for each node can be calculated. The error term measures how much each node is responsible for the errors in the output and is used to update the coefficient of a certain node. After each iteration, the NN coefficients will be updated with the back-propagation algorithm reducing the cost function. The training procedure will stop when the cost function meets the training requirement. In the experiments, 8 A-scans are used to train the NN, and 6 of the A-scans are used to test the result.

After the NN is trained, it is validated with test input. A test input is supposed to be a signal obtained from the same structure using the same system configuration that has never been used in the training. Figure 5 shows the result of the trained NN performance using feed-forward algorithm. Figure 5b is obtained by extending all the points of the training result to 50 samples corresponding to its original position in the A-scan and stack them together. The result shows that this algorithm can precisely detect the ultrasonic target signal.

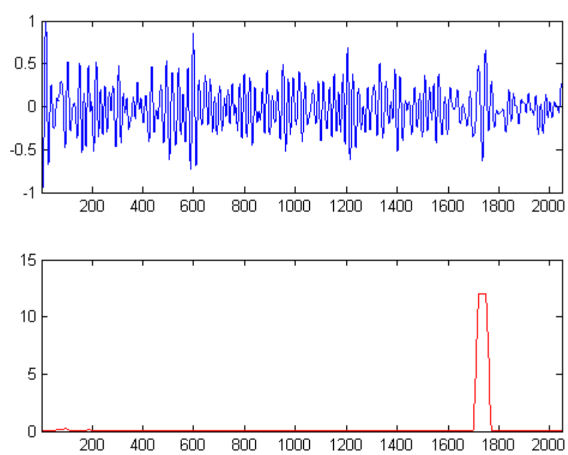

Figure 5. (a) Test Dataset; (b) Target Detection Result

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III. Target Detection using SSP-NN Algorithm

The previous algorithm trains the NN by using the time domain signal. The following NN is trained by using the information from both the time and frequency domains [6]. By conducting Split Spectrum Processing (SSP) on the original A-scan, the signal will be divided into 8 subbands [7]. Equation 1 shows how SSP is implemented. In SSP, the signal will first be converted from the time domain into the frequency domain using Fast Fourier Transform (FFT). Figure 6 shows the spectrum of the original A-scan and the Gaussian filter kernels that are applied to subband the original A-Scan in frequency domain. Note that the majority of the energy in the A-scan is concentrated in the frequency band of 1.5 MHz to 9 MHz. Experiments indicate that the frequency from 1.5 MHz to 6 MHz carries most of the information pertaining to the target echo. Therefore, 8 Gaussian filters ranging from 1.5 MHz to 6 MHz are generated to split the spectrum of the A-scan. The filtered spectrum is then passed to inverse Fast Fourier Transform (iFFT) to recover the subband time domain signals. These 8 subband signals are used for training the NN.

$$s[n](n \in 1\sim1024) \xrightarrow{FFT} S[k]\ (k \in 1\sim1024)$$

$$\xrightarrow[Filters]{Gaussian} \begin{cases} S_1[k] \\ S_2[k] \\ \vdots \\ S_8[k] \end{cases} (k \in 1\sim1024) \qquad [1]$$

$$\xrightarrow{iFFT} \begin{cases} s_1[n] \\ s_2[n] \\ \vdots \\ s_8[n] \end{cases} (n \in 1\sim1024)$$

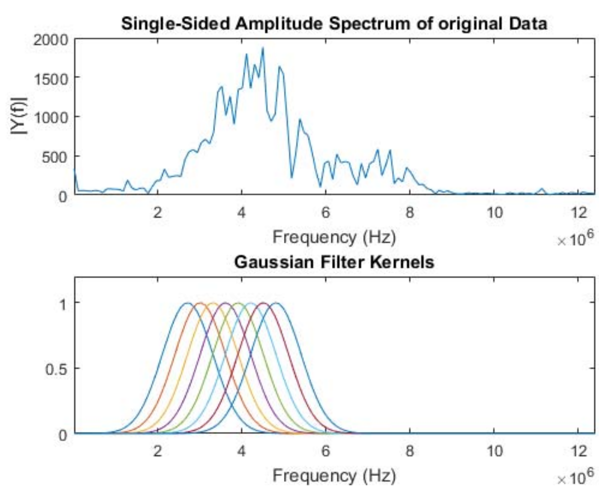

Figure 6. (a) Amplitude Spectrum of A-scan; (b) Split Spectrum Processing Filter Kernels

Prior to training, 8 subband signals are normalized separately to reduce the adverse effect from the absolute amplitude. From each subband signal in the time domain one data point is extracted to form an 8-dimensional data array. Each data array contains 8 points which are $s_1[n], s_2[n], \dots, s_8[n]$ $(n \in 1\sim1024)$. To determine the best method for feeding these 8 subband signals into NN, Embedding Projector is used to project the high dimension data into 3D space. Figure 7 shows the 8-dimension data projected in a 3D space plotted by Embedding Projector. Figure 7a highlights non-target echoes in solid bigger red dots. Figure 7b highlights target echoes in solid bigger red dots. This figure proves that using such datasets for the NN training is achievable. The NN is designed similar to the one presented in Figure 4 but requires less nodes due to less complexity of the input data. The NN has one input layer of 5 nodes, one hidden layer of 8 nodes and one output layer of one node.

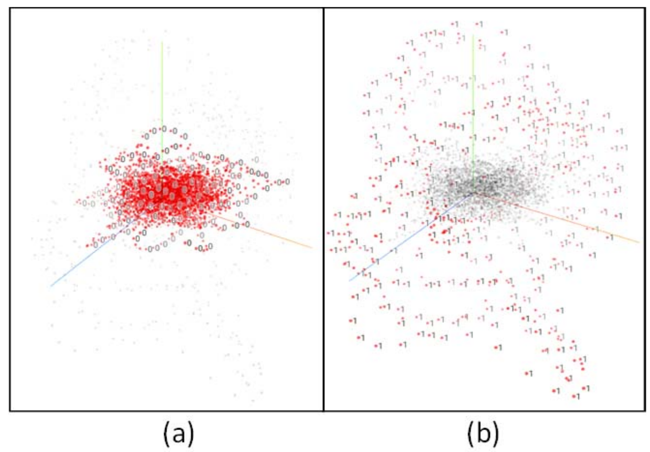

Figure 7. Training Data Plotted in Embedding Projector of TensorFlow

After training the NN for 1500 iterations, Figure 8 shows the target detection performance of the NN. The result obtained from this algorithm is not as pronounced as the result presented in Section II. However, it consumes less computation power to train and test the neural network.

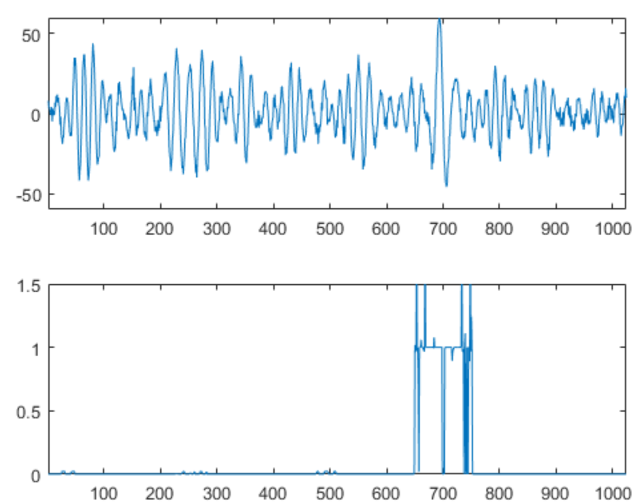

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Figure 8. (a) Test A-scan with Target Echo; (b) NN Target Detection

IV. Conclusion

In this paper, the feasibility of using NN for ultrasonic NDE target echo detection is discussed. Machine learning like the NN is a highly adaptive algorithm. Two NN based algorithms are introduced and results are presented. The first algorithm is based on pattern recognition in time domain. The second algorithm pre-processes the input signal with SSP and trains the NN with both spatial and spectral information. Both algorithms can efficiently and precisely detect the target echo. The trained neural network can be implemented into reconfigurable and programmable system-on-chip hardware platform [8] [9] to achieve real time ultrasonic target echo detection.

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