Ultrasonic Target Echo Detection using Neural Network

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***Abstract* – Ultrasonic Non-Destructive Testing (NDT) and imaging systems has been widely used for industrial and medical applications. In NDT system, detection and characterization of target signal can be extremely challenging because of the complex echo scattering environment and the system noise. In this paper, an algorithm based on Neural Network (NN) is presented to explore the possible solutions for ultrasonic target detection. To reduce the computation load and increase the precision of the NN, signal processing algorithms such as Split-Spectrum Processing (SSP), FIR filtering etc. are applied to the signal. In this study, the algorithm is designed to perform target detection on an ultrasonic testing platform based on Zynq System-on-Chip (SoC) in real-time. The speed of computation is crucial for a real-time testing and signal processing, especially when sampling rate is high. The proposed system can generate, capture and process ultrasonic signals. In this design, the FPGA fabric on the Zynq SoC can be used to accelerate the algorithm and to enable real-time split-spectrum processing followed by neural networks.**

Keywords– Ultrasonic Target Detection, Neural Network

I. INTRODUCTION

Ultrasonic non-destructive evaluation has a wide range of industrial applications. In ultrasonic signal acquisition, the signal is scattered by the microstructure of the material representing the test environment [1]. When performing ultrasonic signal processing, the target signal is always hidden in the scattering noise. Scattering noise is known as clutter; It is a common problem in ultrasonic target detection applications. The clutter is scattered from the original ultrasonic pulse used for testing, it has similar characteristics in frequency domain as the target signal and has similar amplitude compared to the target signal. It means that the clutter is mixed with the target signal and cannot be completely separated by using filtering, maximum detector or other conventional signal processing technologies. This paper presents a solution for ultrasonic target detection and classification based on Neural Network.

Neural Network (NN) is one of the most commonly used machine learning algorithm [2]. It is a nonlinear mapping algorithm that allow the computer to adaptively collect information from many training iterations. NN makes it easier for many complex signal processing applications such as object detection in image, voice recognition and handwriting recognition etc. Instead of developing very complex algorithms, the designers just need to build an NN and train it with large amount of data. The machine will learn from the input and teach itself to characterize the input like the behavior of the training input. Figure 1 is a general NN block diagram. A typical NN is built with one input layer, one output layer and one or more hidden layers. Except for the output layer, each layer has a bias node. A feed-forward computation is to pass a dataset into the NN and get the predicted result.

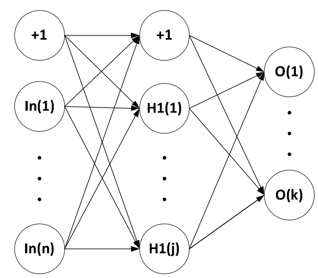

Figure 1. Neural Network Block Diagram

Each node will receive output from all nodes in the previous layer as its inputs. The input will be multiplied with the weight coefficient of the node and be added together. The summation is then passed into sigmoid function to be scaled in the range from 0 to 1. The output of each node is passed to all the nodes in the next layer as input.

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 is calculated after each iteration; It indicates the distance between prediction and true value. The purpose of training procedure is to minimize the cost function. By using the predicted result, an error term for each node can be calculated. The error term measures how much that node is responsible for any errors in the output and is used to update the coefficient of the certain node. After each iteration, the NN coefficients will be updated with the back-propagation algorithm to reduce the cost function. The training procedure ends when the cost function meets the training requirement.

Section II introduces an ultrasonic target detection algorithm based on Split-Spectrum Processing (SSP) and NN. The received signal is divided in to 8 frequency components by applying SSP. Instead of inspecting these frequency components manually to find where the target signal is located. A NN is trained to find the target signal. Section III discussed the application of the NN

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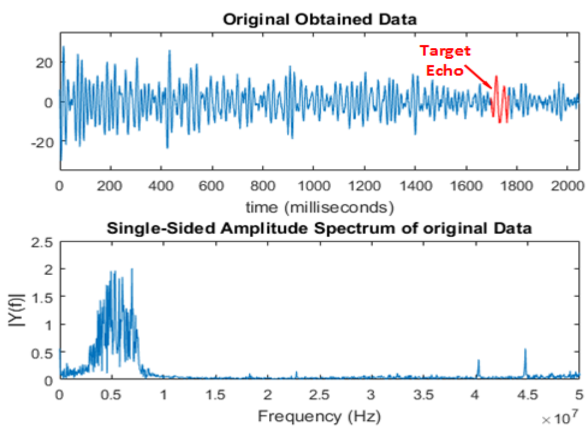
based ultrasonic detection algorithm in an ultrasonic target detection platform based on Zynq SoC. Section V concludes the paper.

II. TARGET DETECTION ALGORITHM

The A-scan shown in Figure 2 (a) is acquired using a broadband ultrasonic transducer of 0.5-inch diameter with 5 MHz of center frequency. The data is sampled at the rate of 100 MSPS, each sample is 8 bits. In the test, a steel block with several defects (holes of 1.5 mm diameter) is used as the target specimen. The position of the transducer, specimen and the defects are already known in the test setup. With this arrangement, the position of the defects in the captured signal can be identified. In Figure 2 (a), the target echo is marked in red. The goal of the ultrasonic target detection is to characterize ultrasonic target echo by training the neural network with sufficient samples. Figure 2 (b) is the power spectrum of the A-scan, the frequency of the signal is ranging from 1.5 MHz to 9 Mhz.



(a)

(b)

Figure 2. (a) Original A-scan with target echo marked (b) Power Spectrum of the original A-scan

To get a better result through the NN algorithm, the frequency component needs to be inspected and separated. One of the most commonly used method for obtaining frequency diverse information is Split-Spectrum Processing [1]. Figure 3 shows the procedures of SSP. The first step of SSP is to convert time domain signal into frequency domain by applying Fast Fourier Transform (FFT) to the A-scan. In frequency domain, different frequency components are separated by using Gaussian masks. Eight Gaussian masks are created to split the frequency domain signal by eight sub-bands. These Gaussian masks covers only the low frequency spectrum (ranging from 1.5 MHz to 6 MHz) to get the best observation on target echo from the original signal [3] . Afterwards, invert Fast Fourier Transform (iFFT) will be applied to all 8 filtered frequency domain signals to convert them back into time domain. In this way, the signal is separated into eight signals with different frequency components. To reduce the interference of the amplitude of different frequency components, these signals are normalized. The normalized signals will be used as the training input of the neural network.

A web application called embedding projector [4] is used to explore the best method for training the NN to yield a desirable precision and performance. Embedding is a map from input data to points in Euclidean space. It is crucial for designing a machine learning algorithm. The input data for a machine learning algorithm usually has more than 3 dimensions. Understanding such data space is hard; By projecting a high dimension dataset to a 2D or 3D space, developers can have an intuitive observation on the input data. A method called Principal Component Analysis (PCA) [5] is the most commonly used algorithm to reduce a complex dataset to a lower dimension to reveal the hidden information. PCA computes the most meaningful basis to re-express the high dimension data. Embedding Projector computes the top 10 principal components and allow users to choose two or three to sketch the data in a 2D or 3D space.

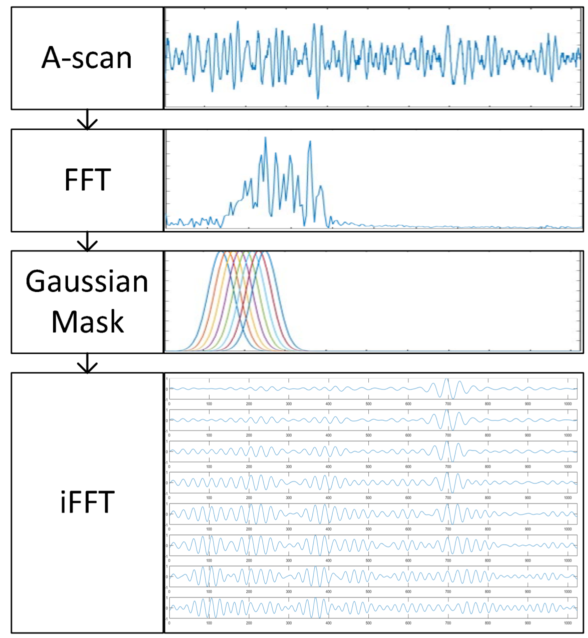
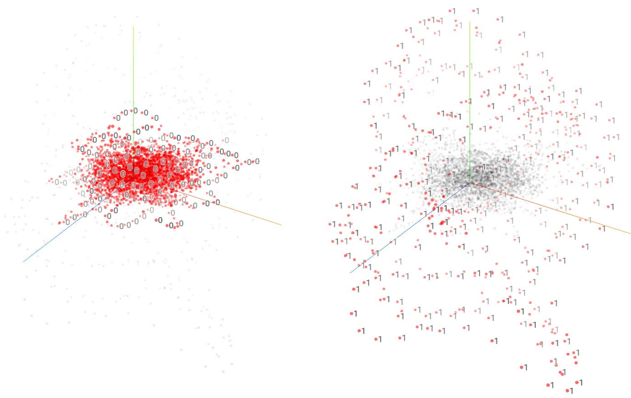


Figure 3. Split-Spectrum Processing (SSP) Results

The eight frequency bands generated by the SSP are used as the inputs of the NN. The input data is 8-dimension and is hard to be observed and analyzed. By feeding the training data to the Embedding Projector, the 8-dimension data will be re-expressed in a 3D space. Figure 4 is the PCA expression of the 4 sets of training data. Each point in the data space is a vector containing eight elements; Each element is a data sample from the normalized frequency component generated by SSP. In the Embedding Projector, the data is labeled as 0s and 1s, non-target samples are marked as 0s and target signal are marked as 1s. Figure 4 (a) highlighted the non-target data samples, Figure 4 (b) highlighted the target data samples. It can be observed that non-target samples are mainly distributed in the middle of the space; Target samples distribute around the non-target samples. A conclusion can be drawn from the PCA expression that it is possible to characterize the target signal from the non-target signal by applying NN.



(a) (b)

Figure 4. PCA representation of 8-Dimensional data space

By processing the training input with different methods and using them as training inputs, it has been found that using absolute value of the training data as input can further separate the target signal and non-target signal. Figure 5 shows the PCA expression of the absolute value of the dataset in a 3D space. Figure 5 (a) highlighted non-target signal points, Figure 5 (b) highlighted target signal points. As it can be easily observed, using absolute value as the training input makes it easier to characterize the target signal.

(a) (b)

Figure 5. PCA representation of 8-Dimensional data space

I utilized 10 ultrasonic A-scans for training and testing. Each A-scan contains 1024 data samples. Target echo in the A-scans are marked as '1' manually for training the neural network. Four sets of A-scans are used to train the neural network and the others are used to test the trained neural network. The training data have 8.6% target samples and the rests are non-target samples.

Figure 6 shows the NN structure. The NN is implemented by four layers: input layer with eight nodes, first hidden layer with ten nodes, second hidden layer with 8 nodes, and output layer with 1 node. Four A-scans are used to train the NN. Target signal in these four A-scans is marked manually as 1 and non-target signal is marked as 0.

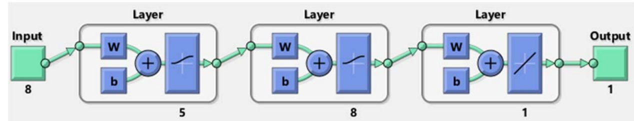
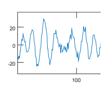


Figure 6. Neural Network Structure of SSP-NN algorithm

After training the neural network with 4096 data samples, the trained network is used to characterize the rest of the data. Figure 7 (a) shows one set of A-scan that is passed into the neural network for feedforward processing. A threshold of 0.8 is used to characterize the output of the feedforward processing and the result is shown in Figure 7 (b). Some of the mischaracterization can be easily removed with median filter. Figure 7 (c) is the filtered result of the characterization output in Figure (b). To give a better detective intuition about the training result, the characterized output is multiplied with the original data; Result is plotted in Figure 7 (d).



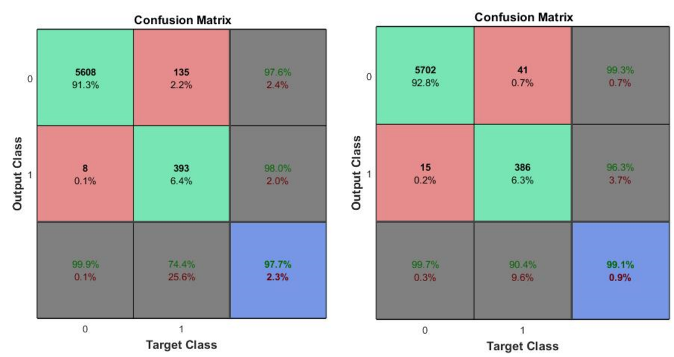
(a)

(b)

(c)

(d)

Figure 7. Feed-forward result of trained NN



(a) (b)

Figure 8. Confusion Matrix Plot of the Training Result

One of the methods to evaluate the training result of a characterization problem is using confusion matrix. Figure 8 (a) is the confusion matrix plot of the training result of the neural network using the data in Figure 4. Figure 8 (b) is the confusion matrix of the neural network trained by the absolute data. After a feedforward processing of the trained neural network, a threshold of 0.8 is used to characterize the target echo. The first training method with data directly from SSP gives an overall 97.7% accuracy and the second training method with absolute value gives 99.1% accuracy. According to the confusion matrix, both methods can recognize the non-target echo very nicely. When characterize the echo target, the first method can recognize 74.4% of the echo signal and the second method can characterize 90.4%, which is a great improvement as expected.

III. ACCELERATION IN PROCESSING PLATFORM

An ultrasonic testing platform [6] is used to obtain the training data for the neural network. This system can generate, capture and process the ultrasonic signal. The system has a Zynq SoC as the main controller and processor. The Zynq SoC has both FPGA and ARM processor on the same chip. The ARM processor is the main controller of the system. The FPGA allows the designers to accelerate the algorithm by utilizing a hardware acceleration unit. Figure 9 is the block diagram of the ultrasonic testing platform system setup. An analog front end takes care of ultrasonic signal generation and acquisition. The acquired signal is sampled by the AD9467 at the frequency of 250 MSPS, with each sample being 16 bit. The sampled data is sent to the FPGA in serial format. A de-serializer on FPGA will convert the serial signal into parallel. Converted data will be buffered and sent to RAM through Direct Memory Access (DMA). The task of the ultrasonic testing platform is to generate the ultrasonic signal, sample the received echo bounced back from the target specimen, process the data and return the result to the user. To process the captured ultrasonic data, one of methods is to transfer the data back to the PC and process it with CPU and GPU co-processing [7]. The communication bandwidth between PC and Zynq SoC is limited by the hardware. So, high fidelity and high compression ratio compression algorithm is required to compress the captured data. An FPGA accelerated DWT based 3D compression algorithm [8] [9] is used in the system to compress the captured data.

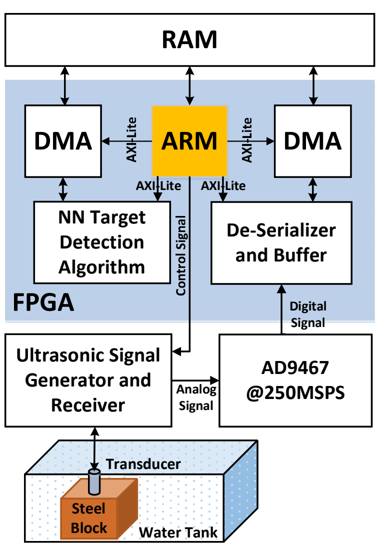


Figure 9. Block Diagram of the System Setup

The signal is sampled at the frequency of 250 MSPS. It is a computationally heavy load for the ARM processor to perform real-time signal processing. Hardware acceleration unit on FPGA can be helpful since real-time processing is required for ultrasonic target detection. On FPGA acceleration unit, processing speed is guaranteed for that parallel processing, pipeline etc. are allowed. In such system, sharing memory between FPGA and ARM processor is implemented by using Direct Memory Access (DMA). DMA is used to transform the data between the RAM and the target detection NN. The NN is pre-trained on the computer, ARM processor will take the training coefficients and load it to the NN hardware acceleration unit on FPGA using AXI-Lite bus. The ARM processor takes control of ultrasonic signal generating, sampling and processing procedures by controlling all the logics by AXI-Lite and other control signals.

IV. CONCLUSION

In this paper, a neural network based algorithm for ultrasonic target detection is presented. The algorithm described in Section II trains the NN with samples from eight frequency components generated by SSP. The training input is in an 8-dimensional space. To gain a better interpretation of the input data space, embedding projector is used to project the high dimension data into 3D space. The algorithm is designed to run on the ultrasonic testing platform based on Zynq SoC. The system can generate high speed and high voltage ultrasonic pulse. The ultrasonic echo is sampled at the speed of 250 MSPS. At such a high sampling rate, the processing speed of the ultrasonic target detection algorithm is crucial when real-time processing is required. The NN can be trained offline on the computer; the trained coefficients will be passed to the feed-forward NN logic implemented on the FPGA through AXI bus. Once the ultrasonic data is acquired by the ADC, the echo will be detected in real time by passing the sampled data into the feed-forward NN implemented on FPGA. This structure allows real-time ultrasonic target detection on Zynq SoC.

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