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A High Performance Ultrasonic System for Flaw Detection

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***Abstract* – In ultrasonic Nondestructive Evaluation (NDE), high frequency acoustic waves are used to test the integrity of materials. The detection of flaw echoes in the presence of high microstructure scattering noise is a challenging problem that requires advanced signal processing methods such as statistical analysis and pattern recognition algorithms. In this study, we designed and implemented a reconfigurable, high performance and low cost ultrasonic NDE platform based on Xilinx ZYNQ SoC. The system can generate high voltage pulses for exciting the ultrasonic transducers, receive the low voltage ultrasonic backscattered echoes, process the acquired data, and transmit and store the processed data to a host computer. in this study, we used machine learning algorithms as an alternate to conventional target echo recognition methods. In particular, Multilayer Perceptron Neural Network (MLPNN) is designed for ultrasonic flaw echo detection. The input to MLPNN is segments of backscattered signals, and regions within the Split Spectrum Processing (SSP) 2D distribution. The experimental results show that MLPNN can detect the flaw echo in the backscattered signal with very high precision.**

Keywords – Ultrasonic NDE System, ZYNQ SoC, Time-frequency Distribution, Neural Network, Flaw Detection

I. INTRODUCTION

Ultrasonic signal is widely applied in industrial, medical and research fields for many imaging and nondestructive testing applications. Ultrasonic nondestructive evaluation (NDE) is an effective and highly practical method to characterize thickness and check internal structure of the test subject with a high precision [1] [2]. In this study, we designed and implemented a reconfigurable, high performance and low cost ultrasonic NDE platform based on Xilinx ZYNQ SoC [3]. This system can generate high frequency ultrasonic pulse and capture the backscattered echoes at the frequency of 250 MSPS. The Field Programmable Gate Array (FPGA) on the ZYNQ SoC allows interfacing high speed peripherals such as Analog to Digital Converter (ADC) to the system through Direct Memory Access (DMA) and Double Data Rate (DDR) memory controller [4]. It can also free the computation power on the ARM processor by accelerating the signal processing with FPGA. With two stepper motors mounted on an ultrasonic testing tank, we can precisely move ultrasonic transducers along x and y axes. The acquired raw data will be pre-processed with time synchronization, band-pass filtering and re-sampling before storage. Applications of ultrasonic flaw detection [5] [6] [7] based on Multilayer Perceptron Neural Network (MLPNN) is introduced for this study. Time domain ultrasonic backscattered signal and its Split Spectrum Processing (SSP) 2D representation are used for training the MLPNN. Experimental results show that the MLPNN can precisely detect and estimate the ultrasonic flaw echo.

Section II of this paper describes the hardware implementation of the ultrasonic NDE system including electronic parts, ultrasonic testing setup, and the raw data pre-processing algorithms. Section III describes MLPNN method for training and detecting the flaw echoes. Section IV concludes this paper.

II. HARDWARE IMPLEMENTATION

In order to acquire the ultrasonic NDE data with pulse-echo method, it is necessary to have electronic components which include Ultrasonic Analog Front End (AFE), high frequency ADC and backend processor for signal processing and data management [8]. The selection of ultrasonic transducer is crucial for properly evaluating the test specimen. Ultrasonic testing system consists of water tank, stepper motors, and Arduino based motor controller for moving the transducer precisely along two axes. A desktop computer is used as the main system coordinator, the signal processor and the controller. In the following subsections, the electronic components, ultrasonic testing unit, experimental setups and the signal processing algorithms will be introduced in detail.

A. Ultrasonic NDE System

Figure 1 demonstrate the system block diagram. The system is built around Xilinx ZYNQ SoC which includes both dual core ARM A9 processor and the FPGA [9]. Ultrasonic AFE consists of ultrasonic pulser (MD1822DB2) [10], Transmit/Receive switch (TX810) [11], voltage-controlled amplifier (VCA8500) [12] and high frequency analog to digital converter (AD9467) [13] is integrated as a programmable and reconfigurable system to generate and receive ultrasonic signals. An Arduino with a motor driver shield that can be controlled through the serial port is used to move the piezoelectric transducer for scanning the material along x and y axes. This allows us to precisely scan the test specimen. The ultrasonic testing data is obtained by collecting data from steel blocks with different grain sizes and embedded flaws at know positions. The training datasets used in this study are obtained using the transducers with a center frequency of 5 MHz at the sampling rate of 250 MSPS with 16-bit resolution. The acquired raw data is parsed and processed with the Python program and trained with neural network models built in the TensorFlow application.

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B. Ultrasonic Experimental Setup

Figure 2 displays the ultrasonic scanning system. With the help of two stepper motors, the ultrasonic transducers can be precisely moved along x and y axes. Users can manually adjust the position of the transducer on the z-axis. Four position limit switches are connected to the system to prevent the system failure caused by unexpected moving instructions. The test subject is submerged under the water to guarantee a good ultrasonic energy propagation. The control of the moving transducer is implemented by using Arduino with GRBL software library [14]. It is an open-source library for Computer Numerical Control (CNC) machine, laser engravers and 3D printers. A customized Python library is implemented in this study to gain full control of the GRBL system to cooperate with the ultrasonic testing system.

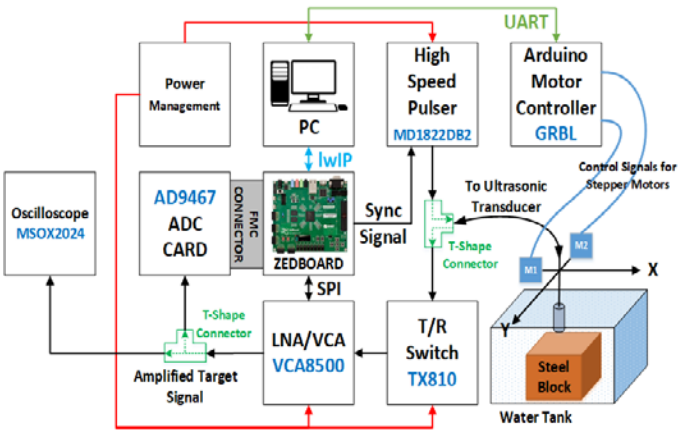

Figure 1. Ultrasonic NDE System Block Diagram

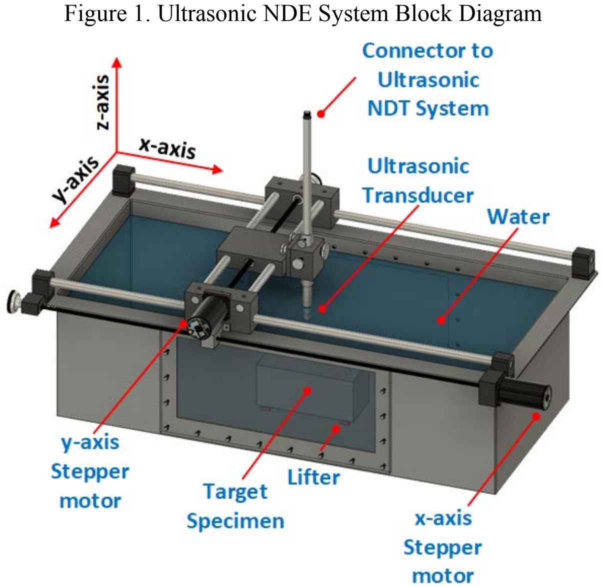

Figure 2. Ultrasonic Scanning System

Figure 3 shows the test setup for acquiring ultrasonic backscattered signal. The transducer used in this test setup is immersion piezoelectric transducer centered at 5 MHz with a standard UHF type of connector. This type of transducer is designed to be used in liquid environment and has an impedance matching layer that deliver higher energy into the water. Ultrasonic backscattered signal is usually acquired in pulse echo type of ultrasonic testing system. As the pulse hits the specimen surface with an angle of 90 degrees, the transducer will receive echoes from front and back surface of the specimen. In between these higher amplitude echoes resides the backscattered signal generated by structural defects such as shrinkage cavities or slag inclusions. Backscattered signal is proven to be an effective indication of grain size, microstructures and flaws, etc. [15] [16]. As shown in Figure 3, a designed delay path between transducer and the upper surface of the specimen is there to reduce the effect of the surface echoes of the specimen on the backscattered signal. A lifter block under the test specimen serves as the same purpose.

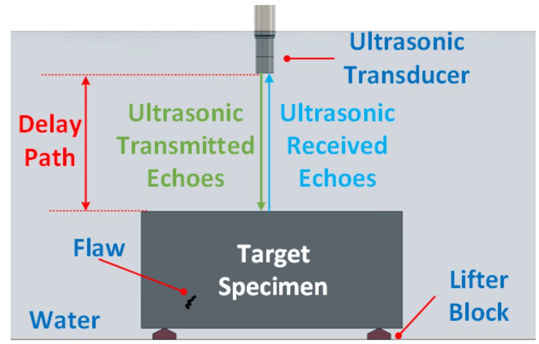

Figure 3. Test Setup for Ultrasonic NDE

Figure 4(a) shows a backscattered signal and Figure 4(b) shows the amplitude spectrum of Figure 4(a). A test steel block with size of 100 mm x 100 mm x 224 mm is placed in the water tank. The magnitude spectrum of the signal in Figure 4(b) shows that the signal is centered at 5 MHz frequency. According to the position of the designed flaw in the target, we compute the position and label the flaw echoes in red of Figure 4(a). This obtained data will be later used for training the neural network.

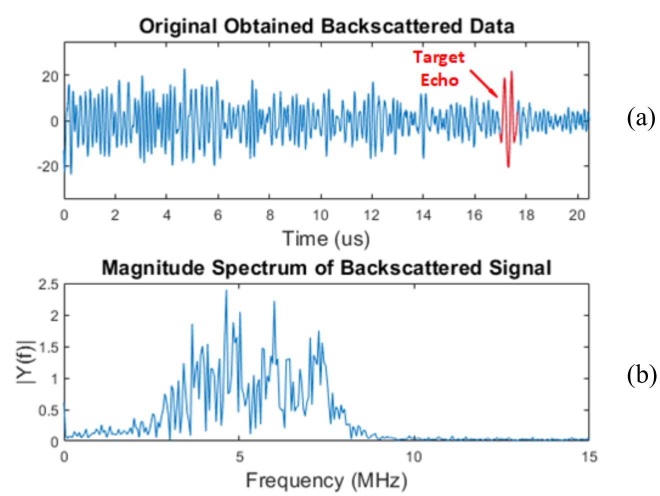

Figure 4. (a) Backscattered Signal (b) Power Spectrum Density of the Signal

C. Raw Data Processing

The signal preprocessing includes, excitation signal synchronization to compensate the mechanical vibration and imperfect system. Signal filtering, DC component removal, resampling, attenuation compensation and finally compression before storage [17] [18]. After the raw data is obtained from the system. We will apply some signal processing algorithms to the signal for preprocessing. This includes filtering, signal resampling, attenuation compensation and DC component removal. After preprocessing of the ultrasonic back scatter signal, we can apply compression algorithm to the signal for a more efficient storage.

Due to the vibration of the moving parts and the transducer moving trajectory is not perfectly parallel with the surface of the testing object, a synchronization in time domain must be implemented to compensate different delays in the acquired signals. This is implemented by correlate the excitation signal with the received signal, by finding the excitation signal position in the received signal, we can add different compensation delays to the received signal to shift the excitation to the same time.

The received signal will have extra frequency components. We are particularly interested in the frequencies from 1 MHz to 10 MHz. A bandpass filter is applied to the signal to filter out the unwanted frequency component. After filtering, the signal will be resampled to 100 MSPS to ensure an optimized resolution and information compactness. Also, for some of the applications such as grain size characterization, attenuation compensation needs to be applied to the acquired signal to extract more information from the backscattered signal.

For those applications that has limited storage area, signal compression algorithms can be applied to the acquired signal. In one of the previously developed compression algorithms based on Discrete Wavelet Transform (DWT) [19] [20], the compression ratio can reach up to 81.25% and the recovered signal has 98% correlation with the original signal.

III. Ultrasonic Flaw Detection with MLPNN

Postprocessing of ultrasonic backscattered signal include time-frequency analysis, flaw echo detection, grain size estimation, etc. [21] [22] [23] [24]. This paper will brief the flaw detection using normalized time domain and SSP representation of backscattered signal segments based on MLPNN as an example application [25] [26].

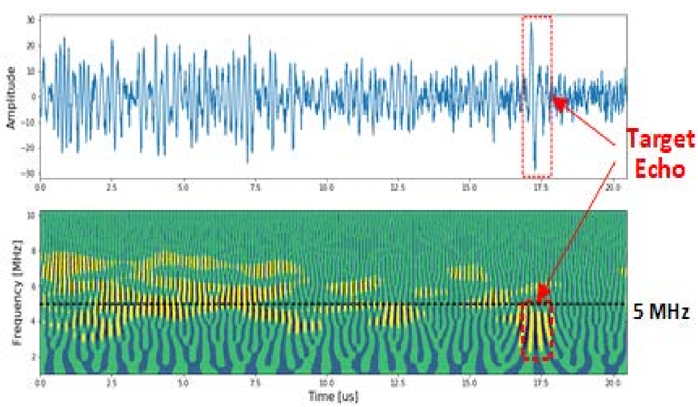

Figure 5. Backscattered Signal and its SSP Representation

Figure 5 shows the backscattered signal plotted in time domain an its SSP representation. As it can be seen from the figure, a target flaw echo can be found at around 17.5 µs. Its SSP representation reveals that the target flaw echo has relatively lower frequency compare to the non-flaw echoes. A window in time domain rolling through the obtained backscattered signals and their SSP representations to divide the signals into segments with the length of 0.5 µs. Fifty samples in time domain can cover approximately 1.8 mm from the target specimen. A total number of 27986 training samples are generated in time and time-frequency domain as training input with labels. Figure 6(a) shows random selected signal time segments in time domain and Figure 6(b) demonstrated the same batch of training input in time-frequency domain. The flaw echoes are labeled in red and the non-flaw echoes are labeled in blue.

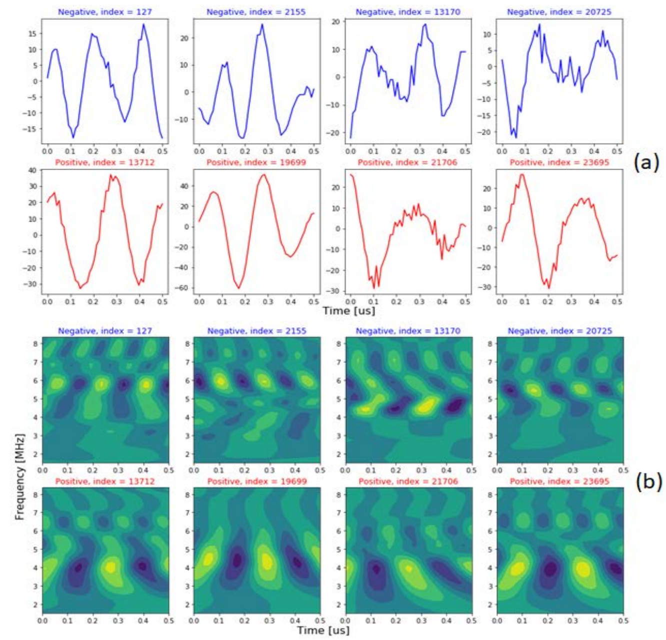

Figure 6. Training Signals in Time Domain

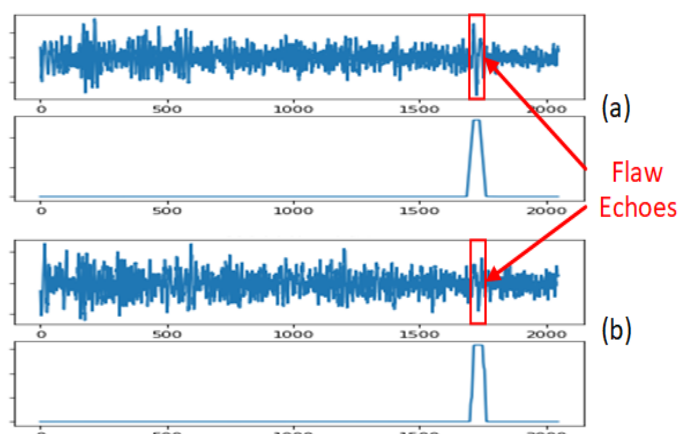

Figure 7. Neural Network Flaw Detection Testing Result

TensorFlow is used in this study for building and training the MLPNN for ultrasonic flaw detection. Both time segments and SSP processed signal segments are used for training two neural networks with the same hyper parameters. After 50 epochs of training for training data generated by time segmentation and SSP algorithm, the time segments trained neural network reach the training accuracy of 99.86% and validate accuracy of 99.27%. The SSP processed data trained neural network has the training accuracy of 99.96% and validate accuracy of 99.31%, which is slightly better than using time segments as training data. Both algorithms can precisely detect the target flaw echoes from the backscattered signal. However, using SSP representation for training the neural network will consume more computation power. Since the training input covers a period of approximately 0.5 µs, a post-processing algorithm is implemented by stacking the data together to restore the time domain information. Figure 7 shows the testing result of the ultrasonic flaw detection algorithm using time segments. Figure 7(a) has a flaw echo with slightly higher intensity which can be precisely detected. Figure 7(b) demonstrate a hidden flaw echo that is detected by the algorithm with lower confidence level.

IV. Conclusion

In this paper, a high-performance ZYNQ SoC based ultrasonic NDE system is designed and implemented to capture and analyze the ultrasonic backscattered signal. This system is real-time, high performance, reconfigurable, low cost, easy to operate and reliable. The proposed system has the capability of real-time data collection and flaw detection with the FPGA on chip. A test setup for acquiring backscattered signal from the test specimen is introduced. An immersion type transducer centered at 5 MHz is used to conduct the experiments. Both preprocessing of the ultrasonic raw data and postprocessing for ultrasonic flaw detection using backscattered signal are introduced. Experimental results clearly support that the algorithm based on neural network can successfully detect the flaw echo in the backscattered signal. The system is capable of precisely detecting highly masked flaw signals (i.e., about zero dB SNR or less).

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