Defect Identification in Concrete Using Deep Learning Technique on Nonlinear Ultrasonic Wave

TONGHAO ZHANG and DIDEM OZEVIN

ABSTRACT

Nonlinear ultrasonic techniques have emerged as a promising tool for detecting defect in concrete. However, detecting the first and higher harmonics of ultrasonic waves in concrete can be challenging due to its complexity and heterogeneity nature characteristics. In this study, a deep learning algorithm was used to improve the accuracy of defect identification. Experiments were conducted on three concrete block samples, including pure concrete and two concrete samples with inclusions. The study utilized an array of R6 sensors as transmitters and an array of R15 sensors as receivers for the measurements. The deep learning algorithm was applied to the wavelet spectrogram of each wave, using 1050 images for training, 116 images for validation, and 292 images for testing. Convolutional neural networks (CNN) were used in the deep learning model. The approach focused on the regions in the first and second harmonic, which are more representative of defect, in the deep learning method. The proposed network consists of several layers that perform different operations to extract relevant features from the input data. The experiments demonstrated the effectiveness of using deep learning algorithms for identifying and classifying defect in concrete. The model achieved an overall accuracy of 94.8% in detecting defect in the concrete samples, with a high precision score for both defect and no-defect identification. This approach successfully detected defect in concrete samples, including the presence of inclusions. As a result, the study showed that deep learning algorithms can be effective in identifying and classifying defect in concrete, with the potential to improve the maintenance and management of concrete structures, enhancing their safety and durability.

INTRODUCTION

Ultrasonic testing (UT) is an active non-destructive testing method to assess the discontinuities within materials [1,2]. When the method is applied to concrete structures, ultrasonic waves are typically generated by a piezoelectric transmitter

Tonghao Zhang, Didem Ozevin, University of Illinois Chicago, 842 West Taylor Street, Chicago, IL 60607, U.S.A

[3,4]. Conventionally, concrete damage is detected by indirectly measuring wave velocity, time of arrival, and amplitude [5]. However, the resolution of linear ultrasonics is constrained by the wavelength of the waves. This limitation becomes particularly pronounced when examining concrete structures, as concrete tends to scatter the waves at higher frequencies, thus further hindering resolution capabilities.

Nonlinear ultrasonic testing (NLUT), on the other hand, advances the method by incorporating the nonlinear behavior of the materials [6]. NLUT enhances the sensitivity for detecting subwavelength defects and improves ultrasonic resolution. One commonly employed method to investigate nonlinearity is the higher harmonic generation method. This technique takes advantage of the distortion of waves and the generation of higher harmonic waves that occur when the initial harmonic signal interacts with heterogeneities within the material. By analyzing these higher harmonics, valuable insights can be gained regarding the nonlinear behavior of the material under study [6]. In the context of concrete, the focus is primarily on the second harmonic wave. The level of nonlinearity is described by the acoustic nonlinearity coefficient β, which represents the proportion of the amplitude of the second harmonic wave to the amplitude square of the first harmonic wave [7,8]. One of the challenges associated with this method is the strong influence of natural heterogeneities and the dispersive characteristics of concrete on the harmonic amplitudes. The presence of aggregates in concrete leads to interference with the ultrasonic wave, causing the medium to behave like a scatterer. The frequency shift observed in the second harmonic of an ultrasonic wave can be attributed to the dispersive nature of concrete. This dispersion effect arises because higher-frequency components tend to propagate faster compared to lower-frequency components. As a result, the different frequencies composing the wave experience varying propagation velocities, leading to a frequency shift in the second harmonic. As a result, the second harmonic may be shifted to slightly higher or lower frequencies than expected [6,7,9], depending on the specific characteristics of the concrete specimen.

To comprehensively analyze the characteristics of ultrasonic waves related to defects in complex concrete materials, relying solely on single feature-based algorithms may not provide sufficient reliability and accuracy. Deep learning, on the other hand, is a method that can be directly applied to time history signals and 2D images [10], eliminating the need for explicit feature extraction from the data. Deep learning has the capability to automatically learn and extract relevant pattern from the input data [11,12], enabling a more reliable analysis of ultrasonic wave characteristics in challenging materials such as concrete.

This paper aims to develop a deep learning framework that can automatically detect the presence of defects in ultrasonic waves. The approach involves training multiple wavelet spectrograms to accurately identify whether a particular wave path contains a defect. Through experiments, the study demonstrates the effectiveness of utilizing deep learning algorithms for defect identification in concrete.

EXPERIMENTS AND CHALLENGES

Experimental Setup

The experiments were conducted using three different concrete specimens. One of the specimens represented pure concrete without any defects and served as the reference, while the other two specimens contained multiple inclusions that simulated defects (as illustrated in Figure 1). The side surfaces of the concrete were equipped with an array of R6 and R15 sensors, and the data acquisition was performed using a PCI-8 data acquisition system manufactured by MISTRAS Group. The received signals were amplified using a pre-amplifier with a 40 dB gain and then filtered using a 20-400 kHz band-pass analog filter. The sensor array consisted of 9 transmitters and 9 receivers, resulting in a total of 81 wave paths within each measurement. A 10-cycle constant amplitude sine wave with frequency at 75 kHz was generated as the transmission signal. The measurements were repeated in both orientations, and each measurement was conducted three times for accuracy and reliability. Consequently, a total of 1458 paths were considered in this study. To train, validate, and test the proposed deep learning algorithm, random selection was used to allocate 72% of the paths for training, 8% for validation, and 20% for the test set.

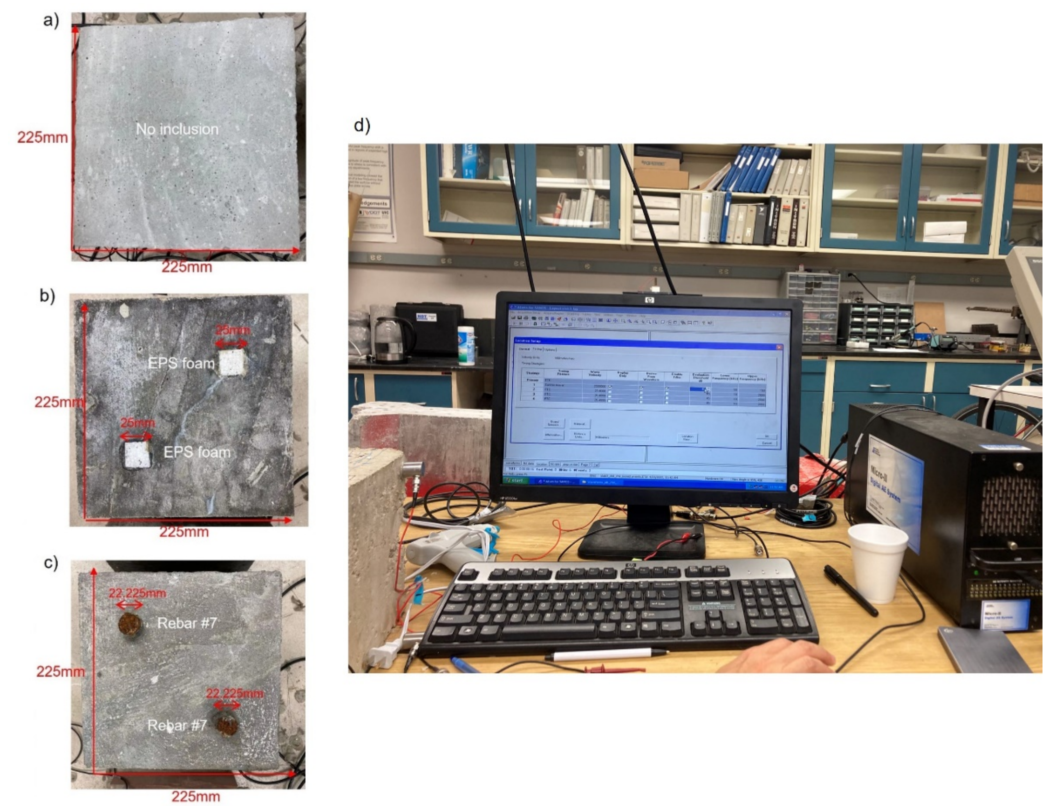

Figure 1. Experimental setup (a) concrete with no defect (b) concrete with foam inclusion (c) concrete with steel inclusion (d) data acquisition system configuration

Challenges of Conventional NLUT

Figure 2a and b present an example of wave propagation path passing through a defect and time history signal obtained by the receiving transducer. To quantify the nonlinearity coefficient β, the time domain signal is transformed into the frequency domain, and the corresponding amplitude at the desired frequency is extracted. As indicated in Figure 2c, the first harmonic frequency of the first harmonic signal exhibits the highest amplitude, while the second harmonic peak is observed in the frequency range of 135 kHz to 155 kHz. It is important to note that the amplitude at 150 kHz experiences a decrease, and the peak corresponding to the second harmonic is shifted to 140 kHz. This observation suggests that relying exclusively on the amplitude at the precise second harmonic frequency may lead to unreliable results and introduce errors in experiments. The frequency shift arises because of the dispersive characteristics of concrete. To tackle this challenge and mitigate the complexities associated with the nature of concrete, a defect identification framework based on deep learning is proposed.

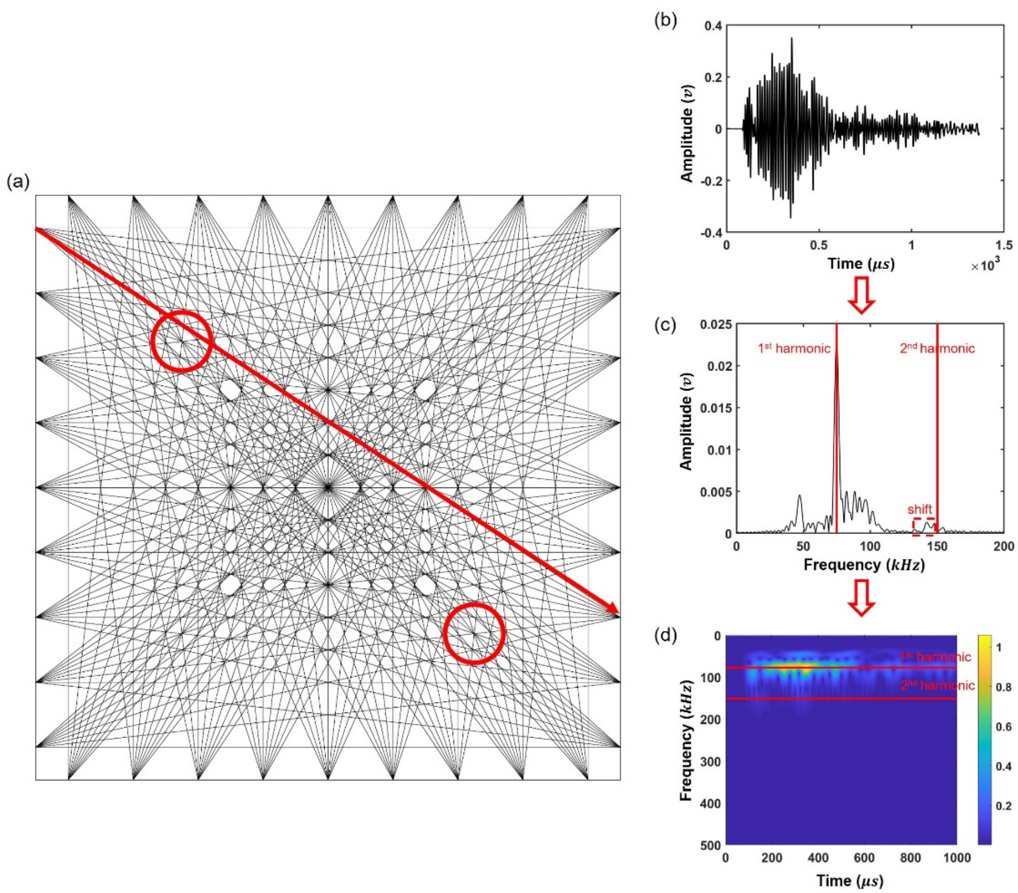

Figure 2. An example of the NLUT results using the second harmonic generation method (a) a wave path through the defect (red circles) (b) the received time history signal (c) frequency spectrum indicating a shift in the second harmonic frequency (d) wavelet spectrogram of the waveform

DEEP LEARNING ARCHITECTURE

Convolutional Neural Network

The Convolutional Neural Network (CNN) comprises multiple layers designed to perform various operations for feature extraction from input data [13,14]. In this study, the input data consists of multi-dimensional images. Unlike conventional neural networks where each layer is one-dimensional, each layer of a CNN has three dimensions: height, width, and depth. For instance, the input image is an RGB image (wavelet spectrogram) with a width of 875 pixels, a height of 676 pixels, and a depth of 3 channels (corresponding to the red, green, and blue color channels).

The CNN architecture is designed specifically for accurate classification of defects in concrete samples. The network integrates wavelet spectrograms obtained from the NLUT method as input images. Each image is labeled based on whether the wave propagates through a defect. If a defect is present in the wave path, the image is labeled as "1”. Conversely, if there is no defect in the wave propagation path, the image is labeled as "0." As depicted in Figure 3, before inputting the image into the CNN architecture, preprocessing steps are undertaken. These steps involve segmenting the spectrogram to include only two specific frequency bands: 145-155 kHz and 70-80 kHz. The frequency range of 70-80 kHz highlights the first harmonic wave, whereas the range of 145-155 kHz is dominated by the second harmonic wave. By segmenting the original image and including only the parts that exhibit greater contrast in identifying the presence of defects in the signal, the robustness of the defect identification algorithm is maximized. In Figure 3b, an image is generated by combining the two frequency bands, resulting in an image with a width of 675 pixels, a height of 90 pixels, and a depth of 3 (representing the RGB channels). To ensure compatibility with the CNN architecture, it is necessary to resize all input images to a standardized dimension. This resizing process ensures that all images have the same dimensions before being fed into the CNN for further processing.

The proposed CNN architecture comprises a total of seven layers, including two convolutional layers, two MaxPooling layers, one flatten layer, one dense layer, and one output layer. The first layer is a convolutional layer with 32 filters of size 3×3. This layer applies these filters to the input spectrograms, convolving them to capture local patterns and features. The Rectified Linear Unit (ReLU) activation function is applied, introducing non-linearity to enhance the network's capacity to learn intricate representations. After the convolutional layer, a MaxPooling layer is introduced. The purpose of this layer is to downsample the feature map, reducing its spatial dimensions while preserving the important signal features. By reducing the spatial dimensions, the MaxPooling layer helps decrease the computational cost and allows the network to focus on the essential information within the signal. This process is repeated once more, incorporating another convolutional layer and a subsequent MaxPooling layer, but this time utilizing 64 filters instead of 32. These steps help to further extract more intricate patterns and features from the preprocessed images. A flatten layer is introduced next to transform the 2D feature map into 1D vector, allowing for the subsequent fully connected layers to process the extracted features. Once the features are flattened, they are forwarded through a dense layer consisting of 64 neurons. This layer establishes connections among all the neurons in

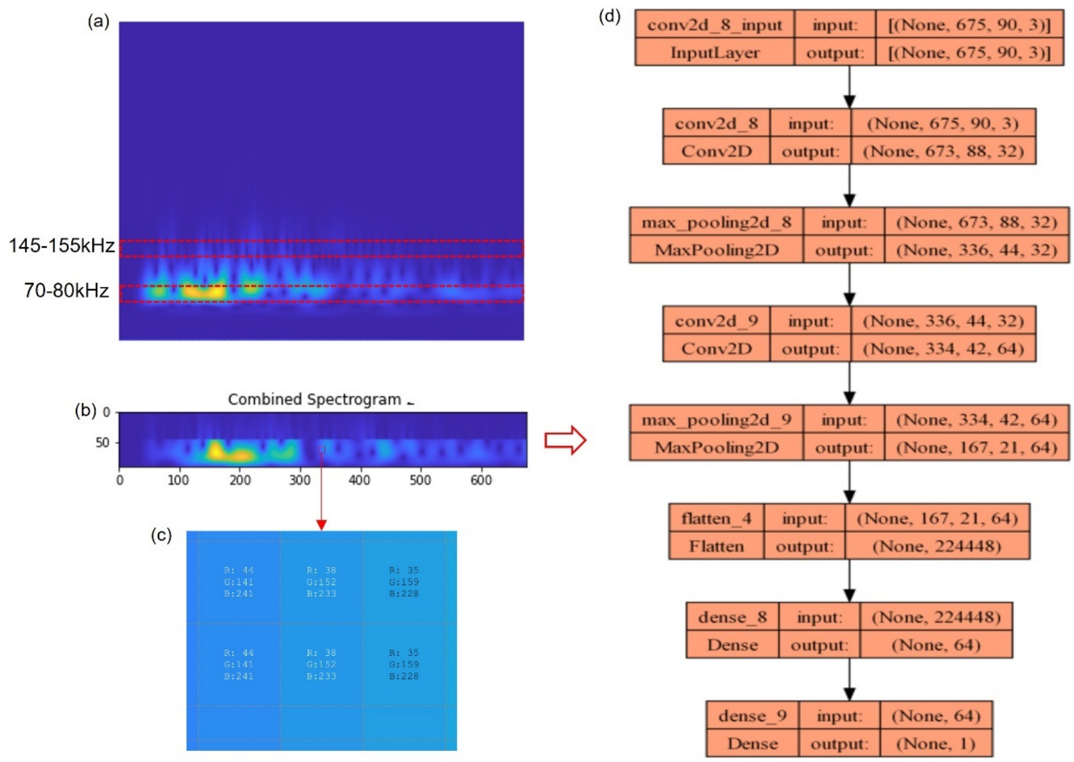

Figure 3. The schematic of the CNN architecture (a) wavelet spectrogram obtained from each wave path (b) the input image of combined spectrogram segmentation (c) the RGB image pixel information (d) the CNN architecture network layout

the previous layer and the following layer. By integrating features from various regions of the input spectrogram, the dense layer acquires knowledge of higher-level representations. Finally, the output layer comprises a solitary neuron equipped with a sigmoid activation function. This function determines the probability of a defect being present in the concrete sample. The sigmoid activation guarantees that the output falls within the range of 0 to 1, indicating the level of confidence in the classification of defects.

In summary, the proposed CNN framework utilizes deep learning with multiple layers to automatically detect defects in concrete. The framework has the capability to learn and extract meaningful information from the input data, enabling accurate identification of defects.

RESULTS AND DISCUSSION

The CNN architecture described above was applied to the ultrasonic signals obtained from three concrete samples shown in Figure 1. The dataset consisted of samples with both defect and no-defect ultrasonic paths. The results as shown in Figure 4 demonstrates the effectiveness of the defect classification. Figure 4a presents the relationship between the batch size (number of input spectrograms from two classes as defect and no-defect) and the prediction accuracy, revealing that the optimal batch size should be chosen to maximize accuracy. The results indicate that a batch size of 16 reveals the highest accuracy in predicting the defect classification. The learning curve was analyzed to observe the training loss and validation loss as the model undergoes multiple training epochs. Each epoch represents a complete pass of the entire training dataset through the neural network, allowing it to learn and update its parameters iteratively. The results shown in Figure 4b indicate that the model successfully learned the underlying patterns without overfitting. Both the training and validation loss exhibit a decreasing trend from the 1st to the 14th epoch, suggesting that the model improved its performance over time. However, after the 15th epoch, the loss function started to increase, indicating that the model may have started to overfit the training data. The results provide valuable insights for selecting the proper hyperparameter to ensure the model performance.

The confusion matrix further reveals the model's performance by showing the counts of true positive, true negative, false positive, and false negative predictions as shown in Figure 5. The model achieved a high number of true positive and true negative predictions, indicating its ability to accurately classify both defective and non-defective samples. The overall predicting accuracy reached 94.8%, with a precision of 95.1% for detecting defects and 94.6% for detecting no-defects. These research findings highlight the effectiveness of using proposed CNN framework for accurate defect detection in concrete samples.

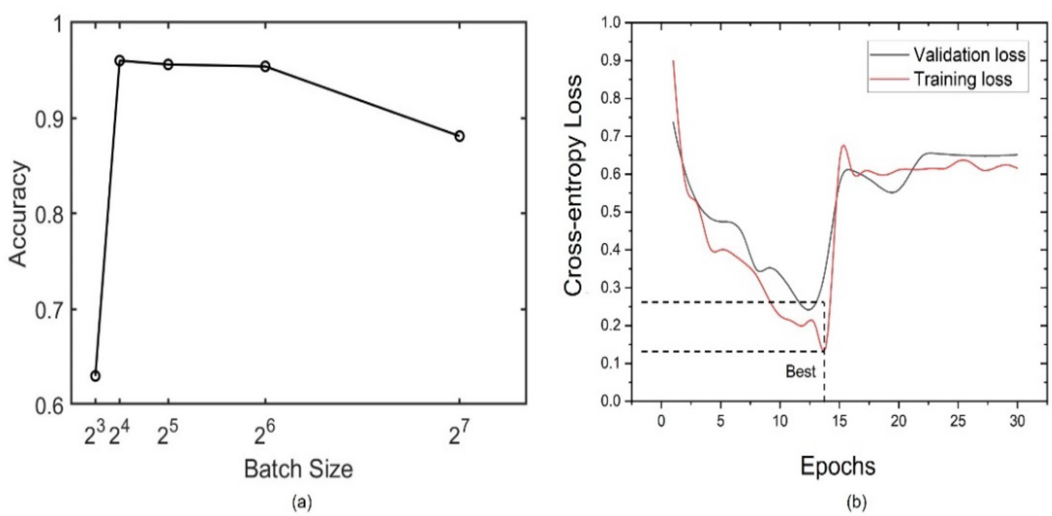

Figure 4. (a) The accuracy variation with respect to batch size and (b) the learning curve of the proposed convolution neural network

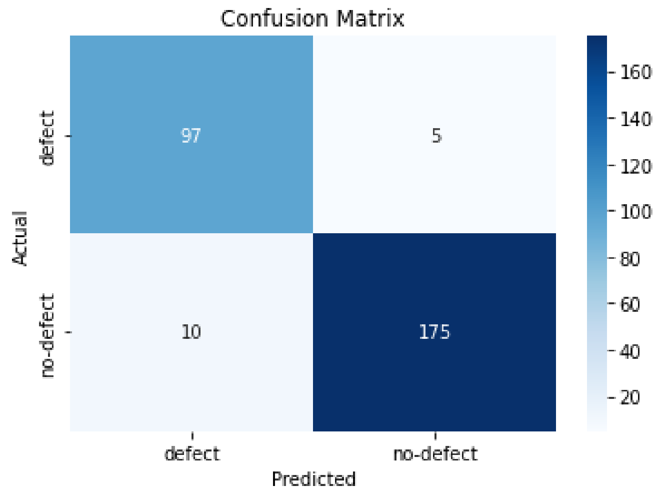

Figure 5. Confusion matrix of the convolution neural network for predicting the presence of the defect in concrete

CONCLUSIONS

Nonlinear ultrasonic testing (NLUT) of concrete poses the challenges to accurately detect the defects due to the heterogeneous and dispersive nature characteristics of concrete. To address the issue, deep learning based NLUT defect identification is implemented. Convolutional neural networks are employed to identify the presence of the defects in ultrasonic paths. The input to the network is a set of segmented wavelet spectrogram images of the ultrasonic signals obtained from each wave path. By training CNN on the input data, the model automatically learns wave interaction pattern and dispersive characteristics of the material. The results demonstrate the proposed CNN network enables defect detection in concrete with accuracy of 94.8%. To extend the application of the proposed architecture, future studies aim to leverage the numerical simulation to generate additional training data. The use of recent techniques such as transfer learning and unsupervised domain adaptation [15] will be explored to align the numerical results with the characteristics of actual experimental data, thereby advancing the defect detection concrete structures.

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