Data Compression for Ultrasonic Microstructure Scattering Signals using Unsupervised Neural Networks

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Abstract*— Ultrasonic Nondestructive Evaluation (NDE) has been extensively used to characterize the microstructure of metallic structures for early exposure of materials integrity. However, industrial NDE requires the processing, storage, and real-time transmission of large volumes of ultrasonic data. Therefore, it is indispensable to compress ultrasonic data with high fidelity. In this study, we explore the development of Unsupervised Learning (UL) based Neural Network (NN) models for massive ultrasonic data compression and an innovative multilayer perceptron residual autoencoder: Ultrasonic Residual Compressive Autoencoder (URCA), is introduced to compress ultrasonic data with high compression performance. This URCA can be fast-trained and utilizes the sparsity penalty with residual connection to optimize compression performance. UL-based NNs allow for memory-efficient training and rapid online augmentation of the model. To examine the results, a high-performance ultrasonic signal acquisition system was assembled to automatically collect ultrasonic data from heat-treated 1,018 steel blocks for microstructure characterization. Compression performance is analyzed based on compression ratio, reconstruction accuracy and model training time. The reconstruction accuracy was measured using the Structural Similarity Index Measure (SSIM) and Peak Signal-to-Noise Ratio (PSNR). By training the URCA NN for a high reconstruction performance of 0.96 SSIM, we obtained 91.25% memory space-saving. For a higher compression performance of 0.80 SSIM, we obtained 96.04% memory space-saving.

Keywords*— *Unsupervised Neural Networks, Ultrasonic NDE Data Compression, Compressive Autoencoder, Sparse Dictionary Learning, Incremental Learning, Microstructure Characterization

I. INTRODUCTION

Steel material microstructure characterization using ultrasonic nondestructive evaluation (NDE) has been broadly used for early exposure of structural and physical material integrity [1]. The ultrasonic microstructure scattering signals and signal attenuation can be used to estimate the grain size [2]. Because of the statistical variation in the scattered energy as a function of depth [2], the ultrasonic scattering signal is characterized for grain size estimation. However, industrial NDE requires high-performance processing and real-time transmission of massive ultrasonic data. Therefore, ultrasonic data compression with high fidelity is indispensable. In traditional algorithms for ultrasonic data compression, such as Discrete Wavelet Transform, Walsh-Hadamard Transform, and Discrete Cosine Transform, these methods can compress ultrasonic data with high accuracy [3]-[7]. Recently, machine learning methods are emerging in various ultrasonic applications to automate NDE inspection, such as material microstructure characterization, flaw detection, and data compression [8]-[11]. In machine learning, unsupervised learning (UL) learns principal latent information in unlabelled data with minimal human supervision [12]. Advanced UL methods include Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Sparse Dictionary Learning (SDL) [13][14]. UL methods can compress ultrasonic data with high performance and allow for memory-efficient training and rapid online augmentation of the models by using stochastic training such as the incremental learning mechanism [14]. In this study, we explore the development of UL-based NNs for massive ultrasonic data compression and propose an innovative multilayer perceptron residual autoencoder: Ultrasonic Residual Compressive Autoencoder (URCA), to compress ultrasonic data with high performance. This URCA NN can be fast-trained and utilizes the sparsity penalty with residual connection to optimize compression performance. For performance comparison, we trained several UL models using the incremental learning method and analyzed the overall compression performance with this URCA NN. The compression performance is analyzed and compared based on memory space-saving, reconstruction accuracy, and training time. Memory space-saving indicates the reduction in memory storage size relative to the observed ultrasonic data and is measured as the difference between 1 and the reciprocal of the compression ratio. The compression ratio is calculated as the size of the measured ultrasonic data divided by the size of the compressed data. The reconstruction accuracy is measured by using the SSIM [15] and PSNR. The subsequent SSIM index is between 0 and 1, and a higher SSIM index represents better reconstruction. To examine the results, a high-performance ultrasonic NDE signal acquisition system was assembled to automatically collect data from heat-treated 1,018 steel blocks for microstructure characterization.

In this paper, Section II presents the intelligent ultrasonic NDE the system used to acquire ultrasonic microstructure scattering signals for data compression. Section III presents the URCA NN and UL models for ultrasonic data compression. The compression performance of the UL algorithms is analyzed and compared. Section IV concludes this paper.

II. ULTRASONIC TESTING PLATFORM

The high-performance ultrasonic NDE signal acquisition system we built to obtain the ultrasonic data is shown in Figure 1. This data acquisition platform consists of a water tank for testing specimens. This water tank is mounted with two stepper motors to automate the ultrasonic data acquisition procedure. To guarantee good ultrasonic energy propagation, the specimen was immersed underwater to experiment. The broadband piezoelectric ultrasonic transducer with 5MHz central frequency was used to acquire ultrasonic signals. In addition, an ultrasonic pulser/receiver, Panametrics Model 5052PR, was used as the signal generator and echo receiver. To monitor the data acquisition procedure, an oscilloscope, Keysight MSOX2024A, was used for high-frequency signal synchronization from the pulser/receiver. In this study, we acquired a volumetric data cube with the size of 200×200×2400 from one heat-treated 1,018 steel block. This observed data cube was converted into a 2D data matrix for compression using the URCA NN and UL models.

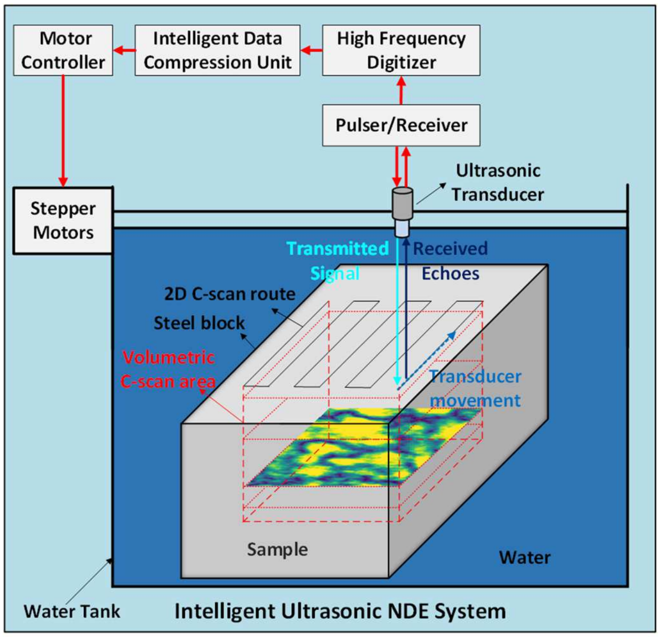

Figure 1. Ultrasonic NDE System for Data Acquisition

III. ULTRASONIC DATA COMPRESSION USING UNSUPERVISED NEURAL NETWORKS

The volumetric ultrasonic data from one heat-treated 1,018 steel block was acquired for microstructure characterization. The data contains the microstructure scatting features of the specimen and is used to train the URCA NN and UL models for data compression. In the following three subsections, the URCA NN and UL models are introduced for ultrasonic data compression. For compression performance comparison, we have two compression targets: 1. high compression ratio with an SSIM of 0.8, which includes most ultrasonic microstructure scatting features; 2. high reconstruction accuracy with an SSIM of 0.96. The reconstruction accuracy is measured by using the SSIM and PSNR. The training was implemented on the Google Colab 26GB RAM Tesla T4 GPU.

a) Ultrasonic Residual Compressive Autoencoder (URCA)

URCA is a lightweight multilayer perceptron autoencoder [16] and can be fast-trained for memory-efficient learning and rapid online augmentation of the model. UL-based NNs such as URCA learn principal latent patterns of unlabeled data from an encoder to a decoder to reconstruct training data based on the compressed latent patterns. This URCA utilizes the sparsity penalty with residual connection [17] to optimize compression performance.

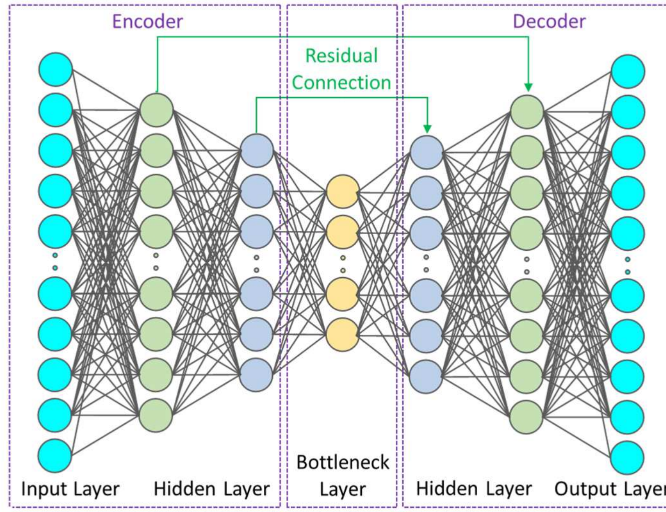

Figure 2. Ultrasonic Residual Compressive Autoencoder

Figure 2 shows the schematics of the URCA architecture. This NN is fully connected and consists of a 4-layer dense encoder followed by a 4-layer dense decoder architecture. To enhance compression performance, the LeakyReLu [17] activation and residual connection [17] are used to optimize this NN. The residual connection improves the reconstruction accuracy to accelerate the training implementation. In addition, the Adam [17] algorithm is applied to optimize the training procedure and requires little memory space for computationally efficient training. In this study, we trained URCA NN using 500 epochs with a batch size of 256. The objective function is measured by using the mean squared error.

b) Principal Component Analysis (PCA)

The PCA method aims to find principal latent patterns in high-dimensional data and represent the data with fewer principal components (PC's). These PC's are trained by minimizing the mean squared error between the observed data and reconstructed data and maximizing the data variance in training. The first PC contains the maximal data variance and each succeeding PC has an incremental decreasing contribution to the total data variance. Every PC is orthogonal to each other. In this study, PCA is used to compress ultrasonic data by reducing redundant data information.

To further optimize computation and memory efficiency in training, we trained the Incremental-PCA to compress ultrasonic data using a mini-batch fashion. The Singular Value Decomposition (SVD) algorithm was applied to implement this training to find PC's in ultrasonic data. Compared with PCA, the SVD is less prone to numerical noise because the covariance matrix does not need to be calculated. In addition,

c) Sparse Dictionary Learning (SDL)

The SDL method is used to find sparse latent patterns in ultrasonic data by training optimized base vectors. These base vectors form a dictionary which is learned in training. Compared with PCA, SDL allows more flexibility for learning sparse representations of ultrasonic data as the learned dictionary is not required to be orthogonal. In addition, to achieve efficient compression on large datasets, we trained the SDL by dividing the ultrasonic data into small batches using the incremental learning mechanism. This stochastic training scales up well for large datasets and allows the model to dynamically adapt to compress new data for in-service ultrasonic NDE. In this study, we trained the SDL and Incremental-SDL to compress ultrasonic data into a few sparse components.

TABLE 1. PERFORMANCE COMPARISON FOR HIGH COMPRESSION RATIO
SSIM: 0.8

Model (# of Dictionaries)	Memory Space Saving	PSNR (dB)	Training Time
PCA (100)	95.83%	29.26	12.08
Incremental-PCA (102)	95.75%	29.44	38.25
Incremental-SDL (250)	89.58%	29.39	125.18
URCA Neural Network (95)	96.04%	30.14	2045.18

TABLE 2. PERFORMANCE COMPARISON FOR HIGH RECONSTRUCTION ACCURACY
SSIM: 0.96

Model (# of Dictionaries)	Memory Space Saving	PSNR (dB)	Training Time
PCA (227)	90.55%	30.98	19.64
Incremental-PCA (234)	90.25%	30.78	56.12
Incremental-SDL (500)	79.17%	31.46	153.69
URCA Neural Network (210)	91.25%	31.18	2516.87

Table I and Table II show the performance comparison by using UL models and the URCA NN to compress data for ultrasonic microstructure scattering signals. In Table I, for a higher compression performance of 0.80 SSIM, we obtained the highest 96.04% and the average 94.30% memory space saving by training the URCA NN and UL models respectively. In Table II, for a higher reconstruction performance of 0.96 SSIM, we obtained the highest 91.25% and the average 87.81% memory space saving by training the URCA NN and UL models respectively. The PCA outperforms other UL models in training time. The URCA NN achieves the highest compression ratio and reconstruction accuracy. Although URCA NN takes the longest time to train compared with other UL models, the training time is much faster compared with most state-of-art NNs, such as deep-CNNs [17], and LSTM-autoencoder [16]. The training time includes the time to train the models and is measured in seconds.

IV. CONCLUSION

In this study, we explore the development of UL-based models and NNs with incremental learning for massive ultrasonic data compression. Several state-of-art UL models are trained and compared based on compression ratio (memory space saving), reconstruction accuracy, and training time. An innovative multilayer perceptron residual autoencoder: URCA, is introduced to compress ultrasonic data with high compression performance. This URCA can be fast-trained and utilizes the sparsity penalty with residual connection to optimize compression performance. UL-based NNs allow for memory-efficient training and rapid online augmentation of the model. To examine the results, a high-performance ultrasonic signal acquisition system was assembled to automatically collect ultrasonic data from heat-treated 1,018 steel blocks for microstructure characterization. Compression performance is analyzed based on compression ratio, reconstruction accuracy, and model training time. The reconstruction accuracy was measured using the Structural Similarity Index Measure (SSIM) and Peak Signal-to-Noise Ratio (PSNR). By training the URCA NN for a high reconstruction performance of 0.96 SSIM, we obtained the highest 91.25% memory space-saving. For a higher compression performance of 0.80 SSIM, we obtained the highest 96.04% memory space-saving.

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