Unsupervised Learning for 3D Ultrasonic Data Compression

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***Abstract*— Ultrasonic testing has been widely used for nondestructive applications because it is inexpensive and has high inspection accuracy. However, massive ultrasonic data generated from the signal acquisition platform limits the performance of ultrasonic applications. Therefore, ultrasonic data compression with high accuracy is significant. In this study, we propose to use unsupervised learning (UL) to compress 3D ultrasonic data. The UL learns principal latent patterns and removes redundant information in ultrasonic data. The latent patterns are used to compress the 3D ultrasonic data. In this study, we propose to use several UL methods: Principal Component Analysis (PCA), Incremental-PCA, Independent Component Analysis (ICA), and Exploratory Factor Analysis (EFA) to learn latent patterns in acquired 3D ultrasonic data. An automatic ultrasonic testbed platform is assembled for ultrasonic data acquisition. By using UL, for high compression performance, we obtained the average 4.25% compression ratio; for high reconstruction performance, we obtained the average 9.67% compression ratio. The reconstruction accuracy is measured using the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM).**

Keywords*— *Unsupervised Learning, 3D Ultrasonic Data Compression, Principal Component Analysis, Independent Component Analysis, Exploratory Factor Analysis; Peak Signal-to-Noise Ratio; Structural Similarity Index Measure

I. Introduction

Nondestructive evaluation (NDE), such as metallic texture inspection, using ultrasonic testing has been widely used to characterize the microstructure of materials [1]. The ultrasonic microstructure backscattering signals can be characterized to estimate the material grain size where the signal intensity is the non-explicit function of average grain size, random distribution of grains, and ultrasonic frequency [2]. However, industrial NDE or medical imaging requires the processing of large amounts of ultrasonic volumetric data due to the process of 3D scanning. And these massive data generated from the signal acquisition platform limits the performance of ultrasonic applications. Traditional compression algorithms in ultrasonic inspection include Walsh-Hadamard Transform (WHT) [3], Discrete Cosine Transform (DCT), and Discrete Wavelet Transform (DWT) [4][5][6][7][8]. The WHT utilizes the unitary and orthogonal transform composed of rectangular waveforms and is simple to be implemented [3] while suffers from low reconstruction accuracy [9]. The DCT uses a sum of cosine functions to represent data and the DWT correlates the input ultrasonic signals with wavelet kernels for data compression [4]. The DCT and DWT can compress the 3D ultrasonic signals with high compression performance but is time-consuming for implementation [9]. Therefore, to enhance the performance of ultrasonic data compression, we propose to use the machine learning method to compress the 3D ultrasonic signals. In ultrasonic inspection, machine learning has been used to estimate grain size by characterizing the backscattered signals [10][11][12] but has seldomly been used for compression of ultrasonic data, particularly the volumetric ultrasonic signals. In machine learning, unsupervised learning (UL) aims to learn latent patterns in unlabeled data with minimal human supervision [13]. Advanced algorithms used in UL to learn principal latent information are latent variable model learning [14] [15], such as PCA [16], and ICA [17]. In this study, we aim to use UL to enhance compression performance for high-performance ultrasonic NDE applications. Several state-of-art UL algorithms are analyzed and compared based on the compression ratio, reconstruction accuracy, and training time. The compression ratio is measured as: the size of the compressed ultrasonic data is divided by the size of the observed data. And the reconstruction accuracy is measured by using the peak signal-to-noise ratio (PSNR) and structural similarity index measure (SSIM) [18]. The resultant SSIM index is between 0 and 1: value 1 indicates perfect structural similarity and value 0 indicates no structural similarity. Thus, a higher SSIM index represents better reconstruction. To examine experimental results, an ultrasonic testbed platform was assembled, and the 3D C-scanning was created to acquire the 3D ultrasonic data from the 1018 steel block for ultrasonic NDE applications.

In Section II of this paper, we present the ultrasonic NDE system setup to acquire 3D ultrasonic backscattered signals. Section III presents the unsupervised learning algorithms for 3D ultrasonic data compression. Performance of the unsupervised learning algorithms to compress acquired 3D ultrasonic data are analyzed and compared. Section IV concludes this paper.

II. Ultrasonic Testing Platform

Figure 1 shows the ultrasonic NDE signal acquisition platform we built to obtain the 3D backscattered signals from the sample of a heat-treated steel block. This platform includes a water tank mounted with two stepper motors for automatic scanning. The specimen was immersed underwater for testing to guarantee good ultrasonic energy propagation. And an ultrasonic pulser/receiver, Panametrics Model 5052PR, was used as the signal generator and echo receiver. In addition, a 5 MHz, 0.375-inch radius, broadband piezoelectric ultrasonic transducer was used to acquire the backscattered signals. And an oscilloscope, Keysight MSOX2024A, is used to synchronize the digital signal from the pulser/receiver to monitor the signal acquisition process. Then the acquired 3D backscattered data was processed by UL algorithms using the data compression unit. In this study, a volumetric data cube of size: 200×200×2400, was acquired from the specimen for the analysis of results as shown in Figure 2. And the acquired 3D ultrasonic data cube was transformed into a condensed 2D data matrix (2D Map also known as B-Scan) for compression using the UL methods.

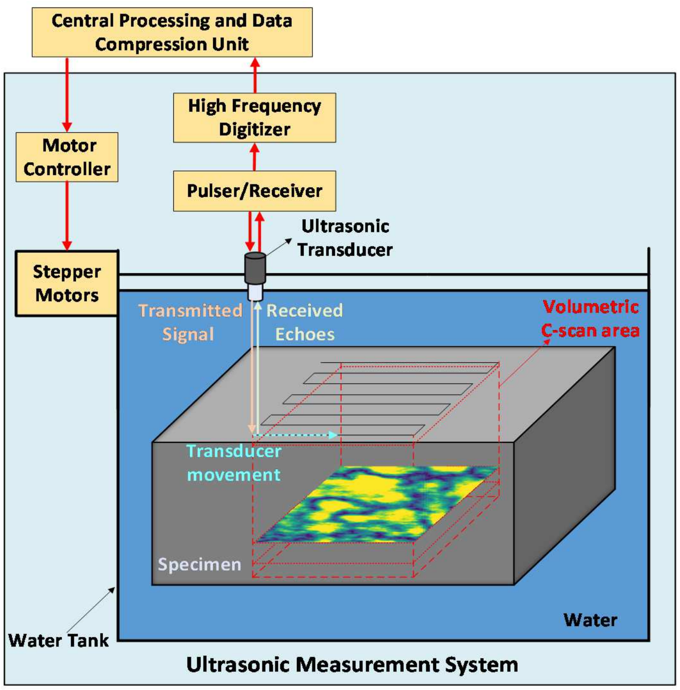

Figure 1. Ultrasonic Data Acquisition Setup

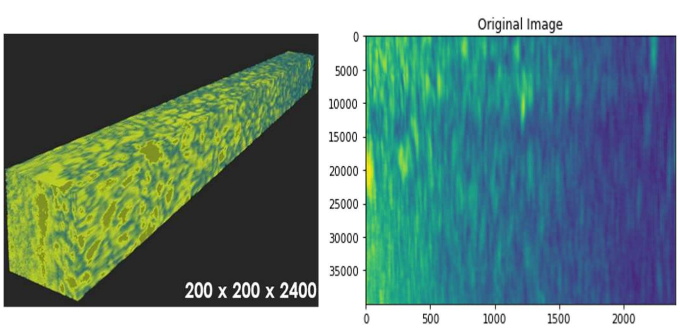

Figure 2. 3D Ultrasonic Data and 2D Map

III. Unsupervised Learning for 3D Ultrasonic Data Compression

The backscattered ultrasonic signals (3D data cube) are acquired to characterize the material microscopic texture from the 1018 steel block and are used to train the UL models for data compression. In the following four subsections, several UL models are introduced to compress the acquired 3D ultrasonic data. By using UL, for compression performance comparison, we set two reconstruction targets: 1. high reconstruction accuracy with the SSIM of 0.96; 2. high compression ratio with the SSIM of 0.8, which includes most signatures of the ultrasonic backscattering features. The reconstruction accuracy is measured using the SSIM and PSNR. The training was conducted on the Intel (R) Core (TM) i7-8750H, CPU@2.20GHz 2.21GHz computer with NVIDIA GTX 1070 GPU.

a) Principal Component Analysis (PCA)

PCA is used to represent high-dimensional data with fewer dimensions, which are called principal components. These principal components are trained by maximizing the variance of training data and minimizing the mean squared errors between the real values and reconstructed values. The maximal variance of the data is contained in the first principal component and each succeeding component, in turn, has the largest variance. Every component is orthogonal to each other to be uncorrelated. In this study, the PCA is used to compress the 3D ultrasonic data with fewer dimensions.

b) Incremental Principal Component Analysis

To optimize memory efficiency and computation in training, Incremental-PCA was trained in a mini-batch fashion to compress ultrasonic data. This training was implemented using Singular Value Decomposition (SVD) algorithm to find principal features in ultrasonic backscattered signals. The SVD closely resembles PCA but suffers less from numerical noise because the covariance matrix does not need to be calculated. Also, dividing the massive ultrasonic data into batches for training allows much more memory efficiency than the PCA as the memory complexity is constant.

c) Independent Component Analysis (ICA)

ICA is used to separate multivariate mixed signals into clusters of independent subcomponents [17]. These independent subcomponents are trained by maximizing the non-Gaussian distribution of training data while maintaining to be uncorrelated. In this study, the ICA is used to compress the 3D ultrasonic data into few independent components.

d) Exploratory Factor Analysis (EFA)

EFA is used to find the linear transformation of lower-dimensional latent factors by removing redundant information and noises [19]. These latent factors are trained by minimizing errors between the real values and reconstruction values for the acquired training data. The main advantage for EFA over PCA is that the EFA can model variance in every direction of the input space independently. In this study, the EFA is used to train the latent factors to compress the acquired 3D ultrasonic data.

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

Model (# of Dictionaries)	Compression Ratio	PSNR (dB)	Training Time
PCA (100)	4.17%	29.24	5.20
Incremental-PCA (102)	4.25%	29.48	50.64
ICA (100)	4.17%	29.25	50.44
EFA (106)	4.42%	29.30	53.10

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

Model (# of Dictionaries)	Compression Ratio	PSNR (dB)	Training Time
PCA (227)	9.45%	30.97	8.98
Incremental-PCA(234)	9.75%	30.87	67.11
ICA (230)	9.58%	30.93	96.29
EFA (237)	9.91%	30.68	117.91

Table I and Table II show the results by using the unsupervised learning models to compress the acquired 3D ultrasonic data. In Table I, for a high compression ratio with the reconstruction accuracy of SSIM: 0.8, we obtained an average compression ratio of 4.25% and PSNR of 29.32. In Table II, for high reconstruction performance with the reconstruction accuracy of SSIM: 0.96, we obtained an average compression ratio of 9.67% and PSNR of 30.86. The PCA outperforms other UL models in the case of the compression ratio, PSNR, and training time. The training time is measured in seconds and includes the time to train the UL model and the time to utilize the trained UL model to compress the acquired ultrasonic data.

IV. CONCLUSION

Unsupervised learning aims to learn latent patterns in unlabeled data with minimal human supervision. Advanced algorithms used in UL to learn principal latent information are latent variable model learning, such as PCA. In this study, we aim to investigate the performance by using the UL to compress the 3D ultrasonic data for NDE applications. To examine experimental results, an ultrasonic testbed platform is assembled to acquire the 3D ultrasonic data from the 1018 steel block for ultrasonic NDE applications. Several state-of-the-art UL algorithms are analyzed and compared based on the compression ratio, reconstruction accuracy, and training time. The future work is to optimize these UL models and utilize the deep learning model, such as the Autoassociative Neural Networks to compress 3D ultrasonic data to enhance compression performance.

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