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A deep autoencoder for ultrasonic image denoising in point contact excitation and detection method

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1. Introduction

Piezoelectric materials, such as Lead Zirconate Titanate Pb ($Zr_xTi_{1-x}O_3$) (PZT) is well known for its superior electromechanical conversion, since it has the larger piezoelectric coefficients. These piezoelectric materials play a vital role in several industrial and military applications, such as optoelectronic, telecommunication, biomedical devices, actuators, structural health monitoring (SHM) and energy harvesting devices [1-3]. PZT ceramics are widely used as transducers in SHM applications as they possess several inherent advantages such as broad-band operational frequency, better electromechanical coupling, easy integrations on the sample surface, and impedance matching with various substrates. SHM is a broader path of study for enhancing the reliability and operational life of various civil and mechanical structures.

Denoising methods can be broadly classified into spatial domain methods and transform domain methods. Spatial filters which are further categorized into linear and non-linear filters utilizes low pass filtering on image pixel values as the noise tends to occupy higher regions in the frequency spectrum[4]. In ultrasonic, the image is normally considered as an accumulation of signals and the existence of noises degrade the image quality. The noisy image reduces the image contrast, edges, textures, object details, and resolution, thereby decreasing the performance of post-processing algorithms. Recently, artificial intelligence (AI) and, more specifically, deep learning (DL), approaches have achieved the state-of-the-art results for many denoising algorithms. Convolutional neural network (CNN) is a well-known dimension reduction technique and has proven to be highly effective in extracting useful features from an image. CNN derived autoencoder is a specific type of feed forward neural network that compresses the input image into a lower dimensional representation and reconstructs the output from the same.

To achieve the problem, we propose a physics-based modeling of noise and generate training samples combined with a deep autoencoder for denoising. We have shown that the proposed method can effectively reduce the noise in experimental data.

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2. Experimental Setup

A detailed description of the excitation and detection principle, working principle, probe fabrication, and the experimental setup has been published before by our group [5-9]. The experimental technique was optimized for an efficient coupling of the electric field with elastic modulus and permittivity of piezo ceramics. This novel experimental technique for point contact excitation and detection based on Coulomb coupling, is developed for the excitation and detection of ultrasonic waves in a piezo-electric materials.

After completing the healthy state experiment, a calibrated damage was introduced using a high-speed diamond drill on the surface of the PZT ceramic. The dimension of the damage was approximately 1.2×1.3 mm2 and 1.5 mm in depth.

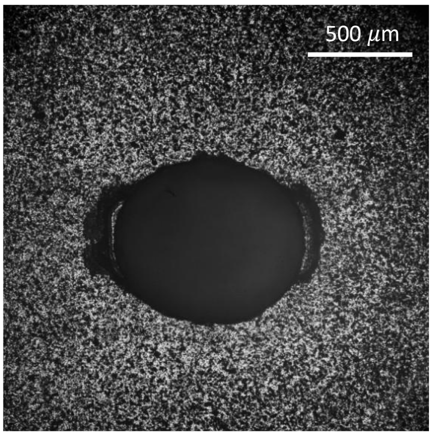


Fig. 1. Optical image for surface flaw for the PZT ceramic sample. The size of the defect is 1.2 mm × 1.3 mm and 1.5 mm in depth.

A default noise adding option from oscilloscope (Agilent 3024A) was employed for adding noise in the excitation signal and performed the imaging.

3. Results and discussion

Autoencoder introduced by Vincent [10], is an unsupervised deep learning algorithm that leverages deep neural networks for dimensionality reduction and feature extraction. It learns to compress the input representation and learns the subsequent reconstruction of the input. It consists of an encoding function, a decoding function, and a loss function which computes the amount of information loss between the compressed and the decompressed representation of the input.

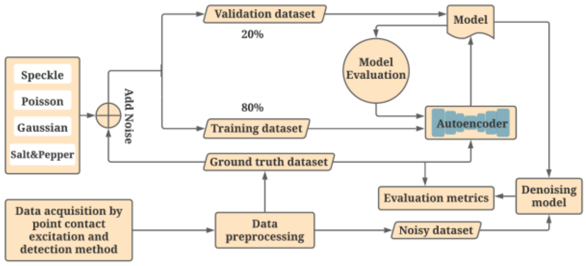
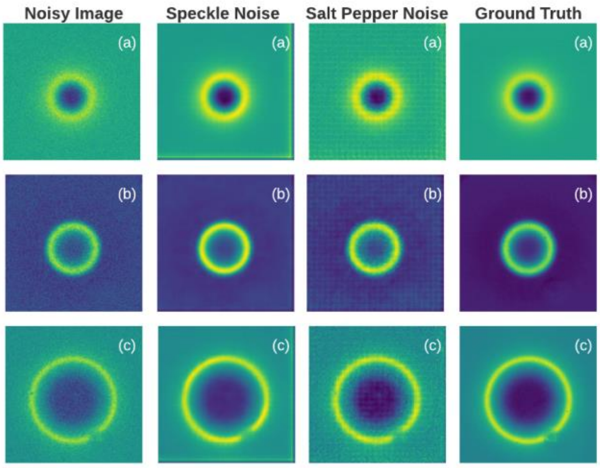


Fig. 2. Flowchart of the data acquisition to denoising process of the ultrasound images

We have extracted 60K (64×64) clean images from the time-series data. We generated 5 different



(A)

Speckle Noise Model	(a)	(b)	(c)
PSNR	26.6851	17.1044	22.3106
SSIM	0.8931	0.5994	0.8151

(B)

Fig. 3A. Noisy, speckle denoised, salt-pepper denoised and ground truth images of ultrasonic waves at three different time frames. **Fig. 3B.** PSNR and SSIM values of speckle denoised images.

training sets containing 48K images each, corrupted with 30% noise of 5 different types namely, speckle, gaussian, Poisson, salt-pepper, and combination of all. A convolutional autoencoder (CA) is trained independently on each training set with noisy image as input and corresponding ground truth image as the target output. We created a validation set with remaining 12K images following the same procedure and used it for tuning the CA hyperparameters. The model is trained with MSE loss over 500 epochs with early stopping using stochastic gradient descent optimizer. We have used different learning rates for each training set, ranging between 0.05 - 0.13. The module is implemented in python using tensorflow framework.

For testing all the 5 CA models, we used original noisy images obtained from the experiment containing 30% noise of unknown distribution. PSNR and SSIM are used as evaluation metrics along with manual inspection for quantitative and qualitative assessment of the denoised images. The combined noise model's performance was highly deteriorated and therefore was not considered for further analysis. Out of remaining 4 models, speckle noise model proved to be superior of all with appreciable PSNR and SSIM values (Fig. 3B). The Salt-pepper noise model had the lowest performance of all 4 models. Both metrics provide different aspects of requirement. PSNR provides higher visual interpretation, whereas the SSIM can be used to measure much finer similarity.

4. Conclusion

In this study, the two-dimensional spatial temporal evolution of waves in the PZT is imaged using point contact excitation and detection method, and a novel deep learning based architecture of convolutional autoencoder is proposed for denoising the ultrasonic images. The PSNR and SSIM metrics in addition to manual inspection show that the model trained on speckle noise performed exceptionally well achieving state-of-the-art results and manifests the immense potential of AI in denoising.

Acknowledgement

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