TinyML-Enabled Unsupervised Ultrasonic Guided Wave SHM Under Varying Thermal Conditions

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***Abstract*—Most machine learning (ML) algorithms reported for ultrasonic guided wave structural health monitoring (GW-SHM) applications, particularly for damage assessment in the presence of time-varying environmental and operating variables, use networks with a lot of parameters, necessitating cloud computing or expensive computing and storage infrastructure. This raises the cost of the solution and may prevent the widespread use of GW-SHM. In this paper, we describe a viable alternative based on TinyML framework, to create lightweight machine learning models that can be instantly deployed on embedded edge devices. We present a practical implementation of this scheme on a custom-designed FPGA-based embedded system for GW-SHM of a honeycomb composite sandwich structure (HCSS) in presence of large thermal variations.**

***Index Terms*—GW-SHM, artificial neural network (ANN), TinyML, unsupervised learning, temperature variation**

I. Introduction

Structural health monitoring (SHM) based on interaction of ultrasonic guided waves (GWs) is enabled by the ability of ultrasonic GWs to propagate long distances without significant attenuation and high sensitivity of the signal amplitude and phase to damages in the structure. However, GWs are also sensitive to variations in environmental and operating conditions (EOCs) and this limits industrial acceptance of such systems [1]. Recently, some deep learning techniques for GW based SHM have been proposed to overcome this limitation, by training the model to learn variations in GW signals due to damage and distinguish them from temperature variations [2]–[4]. Typical deep learning architectures containing convolutional layers result in millions of trainable parameters and require large amount of computational resources for training and inference. There is a need for development of data driven unsupervised algorithms for damage assessment, that could be implemented in edge devices such as microcontrollers [5] and field programmable gate arrays (FPGAs) [6] for data acquisition and inferencing at the edge.

In this paper, we demonstrate a fully integrated SHM system for data collection and damage assessment using a TinyML-enabled unsupervised deep learning framework for GW-SHM. A light-weight artificial neural network (ANN) was trained using features obtained from GW signals collected on undamaged portion (baseline) of a honeycomb composite sandwich structure (HCSS) panel, and then tested on data collected from undamaged as well as two different damaged portions (teflon release film: TRF, and lack of film adhesive: LFA) of the HCSS panel. The light-weight ANN was deployed using TensorFlow Lite framework on the MicroBlaze® reduced instruction set computer (RISC) processor core in the Xilinx Artix®-7 FPGA for damage assessment at the edge. The effectiveness of this method is demonstrated utilizing GW data recorded at various temperatures ranging from $0\,^{\circ}\mathrm{C}$ to $90\,^{\circ}\mathrm{C}$, with pink and white noise added for $20\,\mathrm{dB}$ signal-to-noise ratio (SNR). The proposed approach is a promising step toward a fully integrated data-driven GW-SHM solution.

II. Methodology and Results

Fig. 1(a) shows a photograph of the experimental setup used for this study and Fig. 1(b) shows the HCSS panel instrumented with PZT-5H transducers (dimensions $20\,\mathrm{mm} \times 20\,\mathrm{mm} \times 0.4\,\mathrm{mm}$) for recording GW signals. GW signals for vertical (P15 for baseline, P27 for TRF, and P38 for LFA) and horizontal (P23 for baseline, P45 for TRF, and P56 for LFA) paths were recorded using the Xilinx Artix®7 FPGA-based FPGA board [3]. In the notation Pxy, x denotes the transmitter PZT ID and y denotes the receiver PZT ID. Data were recorded at various temperatures ranging from $0\,^{\circ}\mathrm{C}$ to $90\,^{\circ}\mathrm{C}$. Wavelet transform-based filtering was employed to remove offset from the GW signals, followed by adding white noise and pink noise for SNR of $20\,\mathrm{dB}$ [3] to mimic noisy field conditions (Fig. 1(c)). Next, we manually calculated the following features from the GW signals: mean absolute deviation (MAD), mean, median, variance, kurtosis, skew, crest factor, impulse factor, shape factor, standard deviation, root mean square (RMS), root mean square deviation (RMSD), peak to peak amplitude, and three additional features [7] listed in Table I. The features are not linearly separable, and a simple classifier model is not suitable for it. Fig. 1(d) shows

TABLE I
NON-STANDARD FEATURES COMPUTED FROM TIME-DOMAIN GW SIGNAL (f). GLOSSARY: T: LENGTH OF TIME-SERIES, f_b: BASELINE SIGNAL

Feature	**Expression**
Ratio of signal energy	$\frac{\int^T \lvert f(t)\rvert^2 dt}{\int^T \lvert f_b(t)\rvert^2 dt}$
Damage Index	$\frac{\int^T \lvert f(t)-f_b(t)\rvert^2 dt}{\int^T \lvert f_b(t)\rvert^2 dt}$
Normalized difference of signal energy	$\frac{\int^T \lvert f(t)\rvert^2 dt-\int^T \lvert f_b(t)\rvert^2 dt}{\int^T \lvert f_b(t)\rvert^2 dt}$

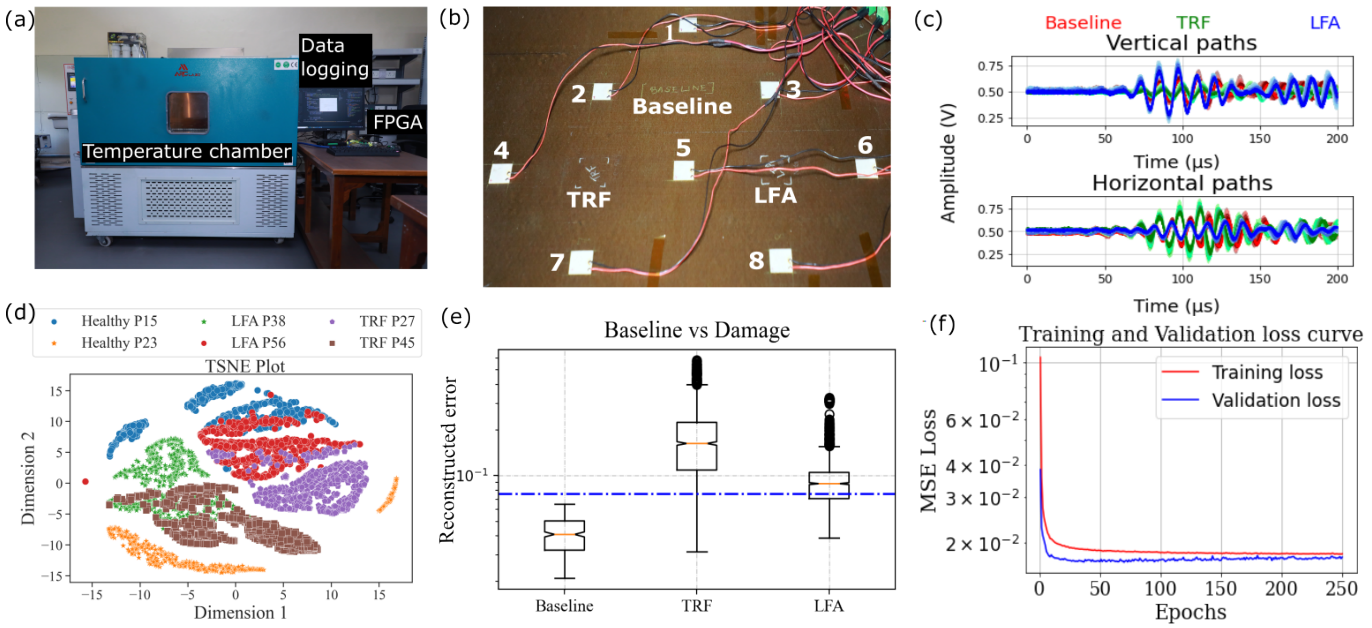

Fig. 1. (a) Experimental setup used for data collection. (b) HCSS panel showing positions of PZT transducers and damaged TRF and LFA) and undamaged (baseline) locations, (c) Noise-augmented data series recorded from 0 °C to 90 °C, for all horizontally and vertically oriented paths passing through baseline, TRF and LFA regions. (d) The features are not linearly separable for damaged and undamaged regions, as seen in the t-distributed stochastic neighbor embedding (t-SNE) plot of training data. (e) Reconstructed error for data corresponding to baseline and damaged regions. (f) Representative training and validation loss curves for the unsupervised learning model.

t-SNE plot for the data that depicts the correlation between the data following feature calculation. The choice of features for edge implementation was based on their sensitivity to damage, computational resources needed for calculations, and memory demand and availability in the embedded system.

An ANN is appropriate for learning how to reassemble the information in unlabeled data. Considering this, it is therefore well suited for unsupervised learning, in which a network is trained utilizing data obtained under normal operating conditions. Data anomalies caused by damage will result in increased reconstruction errors and will consequently be recognized as damaged data. The reconstruction error is quantified by the mean square error (MSE) between reconstructed and input data:

$$MSE = \frac{1}{n} \times \sum_{j=1}^{j=n} (a_j - \bar{a_j})^2 \tag{1}$$

where n denotes number of elements in the input data, a_j is the j^{th} element in the input data and $\bar{a_j}$ is j^{th} element in the reconstructed output data. By training the ANN with healthy data collected at various temperatures, the ANN should be able to learn variation in data due to temperature, and accurately distinguish it from variation due to damage.

The ANN model designed in this work consists of various hidden layers as specified in Table II. The number of neurons in both the input layer and output layer is 16, corresponding to the above-mentioned 16 features. The model was trained on features obtained from data collected on baseline portion of the panel (i.e, paths P15 and P23) under various temperature conditions. The total number of trainable parameters in the model are 9696, which is suitably low for deployment on an embedded platform such as the Xilinx Artix®-7 FPGA. The resource utilization in the FPGA is summarized in Table III.

TABLE II
MODEL ARCHITECTURE

Layer	Number of parameters
Dense (16)	272
Dense (32)	544
Dense (64)	2112
Dropout (64)	0
Dense (64)	4160
Dense (32)	2080
Dense (16)	528
Total trainable parameters	**9696**

TABLE III
RESOURCE UTILIZATION FOR ANN MODEL IMPLEMENTATION ON FPGA

Resource	Available	Utilized	Utilization %
LUT	20800	5463	26.26
FF	41600	4352	10.46
BRAM	50	49	98.00
DSP	90	5	5.55

When the trained model was tested on data collected

TABLE IV
ACCURACY OF ANN MODEL FOR DETECTION OF LFA AND TRF DAMAGE

Threshold	TRF Accuracy (%)	LFA Accuracy (%)
$\mu + 1\sigma$	92	91
$\mu + 3\sigma$	92	71
$\mu + 6\sigma$	78	33

from the two different damaged portions of the panel, the paths containing damage produced higher reconstruction error (MSE) for the model prediction as shown in Fig. 1(e). The training and validation loss curves are shown in Fig. 1(f), which confirm that the model was not over-fitting the data.

The accuracy is calculated by setting the reconstruction error threshold for identifying anomaly as $\mu + \mathcal{X}\sigma$, where $\mathcal{X}$ is a multiplier (set as 1, 3 or 6), and μ and σ are the mean and standard deviation of the reconstruction error for healthy training samples, respectively. During testing, the accuracy for distinguishing TRF damage and LFA damage from baseline signal considering the three threshold values are shown in Table IV (as evaluated by running the model on a desktop computer). Fig. 1(e) shows the result of detecting LFA, TRF and baseline data plot by setting the reconstruction error threshold as $\mu + 3\sigma$. We observed similar accuracy as that reported in Table IV, with average inference time approximately $30\,\mathrm{ms}$ for inference performed on FPGA.

III. CONCLUSION

In summary, we have demonstrated a framework for end-to-end implementation of a GW-SHM embedded system for data acquisition, feature extraction and damage assessment using light-weight unsupervised learning algorithm implemented on an FPGA device. To the best of our knowledge, this is the first reported work on utilization of TinyML framework based compact ML models for damage assessment using ultrasonic guided wave sensing, with significantly smaller model size compared to literature. In future work, we shall investigate methods and algorithms to incorporate online training on the edge device in order to realize fully autonomous GW-SHM systems, and explore strategies to improve the accuracy and robustness of such edge-compatible damage assessment schemes.

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