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Real-time assessment of the mechanical property of foam materials using solitary wave-based deep learning

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ABSTRACT

This study introduces a real-time non-destructive evaluation (NDE) technique for assessing the mechanical properties of form materials using deep learning and highly non-linear solitary waves (HNSWs). The primary objective aims to overcome the limitations of conventional HNSW-based NDE in evaluating polyurethane foams by integrating machine learning models with a modified granular chain crystal sensor for automated quality assessment. The HNSW signals, obtained from the interaction between foam materials with varying densities and a 1D granular chain embedded with a granular crystal sensor, are collected and serve as input data for deep learning models. Convolutional neural networks trained on these HNSW datasets achieved high accuracy in classifying the difference in Young's moduli of foam materials, highlighting the potential of this advanced NDE technique.

1. INTRODUCTION

The integration of deep learning (DL) into a non-destructive evaluation (NDE) system based on highly non-linear solitary waves (HNSWs) has been recently highlighted as feature extraction and classification for the assessment of mechanical properties with enhanced efficiency and precision. The conventional NDE based HNSWs scheme has been implemented using a granular crystal sensor composed of vertically aligned one-dimensional chains of spherical steel beads, and has been

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applied in previous studies for applications such as characterization of mechanical properties of materials (Schiffer 2020, 2019, 2018), the defect detection (Singhal 2017, Yoon 2021, Yoon 2022, Yoon 2023, and Kim 2022), the bone quality assessment (Yoon 2020, Yoon 2021, Yoon 2023, and Kim 2021), and the identification of hydration time and water-to-cement(w/c) ratio in the field of concrete materials (Rizzo 2014, Ni 2012, Rizzo 2016, Nasrollahi 2017, Yoon 2025). Moreover, by expanding upon the conventional HNSW-based NDE framework, recent studies have focused on integrating deep learning to establish automated quality assessment systems, leading to enhanced efficiency, precision, and scalability in the evaluation of material integrity (Kim 2024, 2022, Yoon 2025, 2023).

Motivated by the successful application of HNSWs in NDE, this study aims to develop a real-time HNSW-based NDE method that leverages deep learning to estimate the mechanical properties of porous materials in a fast and reliable manner. A key advantage of the proposed real-time approach is that it eliminates the need for explicit analysis of wave characteristics, such as velocity and amplitude, reflected from the inspection medium. Furthermore, a modified HNSW scheme was employed to overcome the limitations of conventional designs for porous media, replacing the traditional sphere-to-plane contact with a more effective plane-to-plane contact configuration. Among various deep learning algorithms, this study focuses on evaluating the performance of three representative convolutional neural network (CNN) architectures (AlexNet, GoogleNet, and ResNet-18) for classifying the mechanical properties of porous media.

2. COLLECTION OF DATASETS FOR DL

In this study, solid rigid polyurethane foam blocks were used as the inspection medium for classifying Young’s moduli of porous materials. These foam blocks were selected for their compliance with ASTM F1839-08 standards, and their consistent structure, which ensures reproducibility. Each block has a density tolerance of ±10% and dimensional tolerance of ±2 mm. To validate the proposed HNSW-based NDE method and construct a deep learning dataset, experiments were conducted using foam samples with a wide density range (8 pounds per cubic feet (PCF) to 50 PCF, equivalent to 0.13 g/cc to 0.80 g/cc) and uniform dimensions of 3 × 3 × 4 cm. The details of each sample are listed in Table 1.

PCF	8	15	20	25	40	50
Density [g/cc]	0.13	0.24	0.32	0.40	0.64	0.80
Modulus [MPa]	38	123	210	317	759	1148

Table. 1 Details of solid rigid polyurethane foam blocks.

As shown in Fig. 1, HNSW signals were collected from the interaction between the polyurethane foam and a granular crystal sensor. The sensor consists of 20 vertically aligned spherical particles made of AISI 52,000 steel and a bottom hemispherical particle with a flat surface, referred to as the flat-bead (see Fig. 1(a)). While conventional schemes employ 21 identical spherical beads, the design in this study was modified to introduce a plane-to-plane contact configuration, aiming to reduce stress concentration typically induced by sphere-to-plane contact. An incident HNSW was generated by dropping a striker onto the first particle in the chain, which then propagated downward and interacted with the foam sample placed at the bottom, producing a reflected solitary wave, as depicted in Fig. 1(a). Both the incident and reflected HNSWs were captured by a piezoelectric ceramic disk embedded in the 11th particle, converted into voltage signals, and transmitted in real time to an oscilloscope, as shown in Fig. 1(b). A total of 900 HNSW signals were collected, comprising 50 signals from each of the 18 foam samples. These samples represent six different density types, with three samples per density.

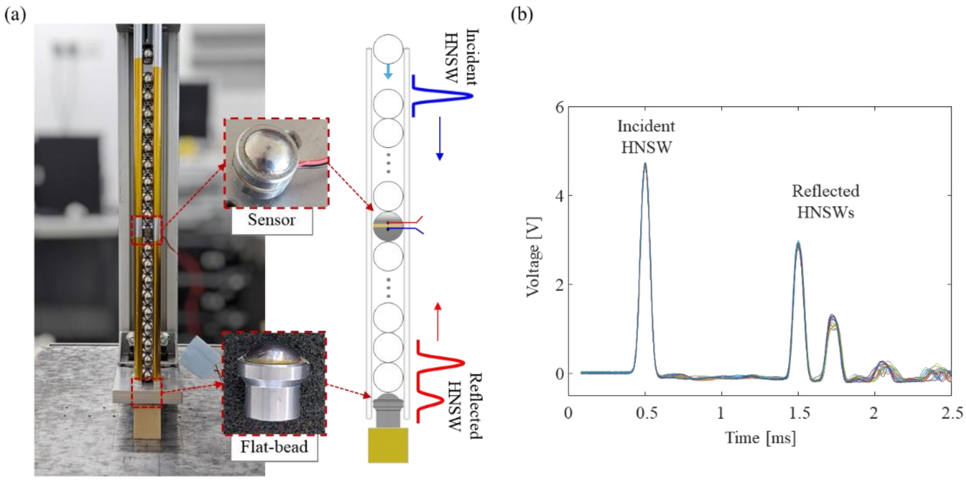

Fig. 1 (a) Experimental setup and schematic diagram of the granular crystal sensor and (b) incident and reflected HNSWs recorded from the sensor.

We established a correlation between Young's modulus and PRW delay based on the observed HNSW data, building on a relationship previously validated in earlier studies [Yoon 2021, 2023]. Notice that the primary reflected HNSWs (PRW) delay is the arrival time difference between incident and the first (primary) reflected HNSWs. The Young's modulus corresponding to each HNSW signal was determined for supervised learning by substituting the peak-to-reflected-wave (PRW) delay into the correlation between PRW delay and Young's modulus. For convenience, the input data were categorized into 11 classes based on Young's modulus at intervals of 120 MPa. Among the entire dataset, 75% was used for training and the remaining 25% for testing.

3. RESULTS AND DISCUSSIONS

We employed three CNN architectures, i.e., AlexNet, ResNet-18, and GoogleNet, to classify Young's modulus from HNSW signals. AlexNet (Krizhevsky et al., 2012) was the first deep CNN architecture to significantly enhance learning performance by increasing network depth and introducing multiple parameter optimization strategies. GoogleNet (Szegedy et al., 2015) was designed to achieve high accuracy with reduced computational cost by utilizing small convolutions and an inception module to drastically decrease the number of parameters. ResNet-18 (He et al., 2016) enables the training of very deep networks by employing residual (skip) connections and extensive batch normalization, effectively mitigating the vanishing gradient problem. For training all three architectures, we used a learning rate of 0.001, a batch size of 128, and stochastic gradient descent with momentum as the optimizer.

Table 2 summarizes the performance of the three CNN architectures for the classification of Young's modulus using HNSW signals. Among the three models, ResNet-18 demonstrated the highest overall performance, achieving an accuracy of 95.56%, a recall of 0.9112, and a precision of 0.9370. AlexNet followed with an accuracy of 93.33%, while GoogleNet achieved a slightly lower accuracy of 91.67%. Although all models performed reasonably well, ResNet-18 exhibited superior capability in distinguishing the mechanical properties, indicating its effectiveness for learning from HNSW signal patterns.

CNN model	AlexNet	ResNet-18	GoogleNet
Accuracy [%]	93.33	95.56	91.67
Recall	0.7644	0.9112	0.7143
Precision	0.8298	0.9370	0.7227

Table. 2 Performance of the CNN architectures for the classification of Young's modules for all three CNN architectures.

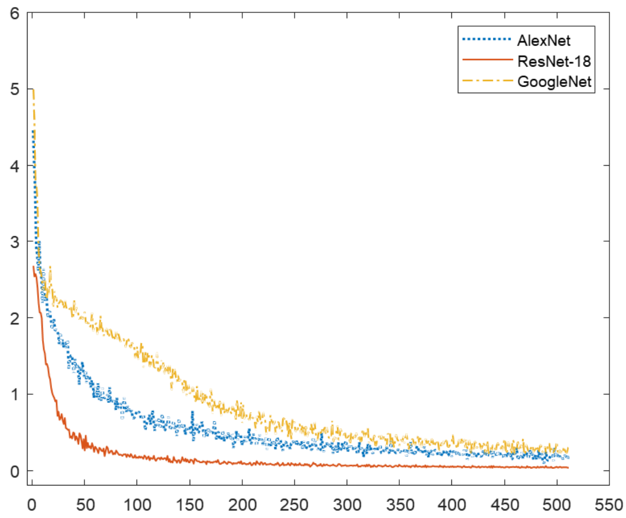

Fig. 3 Training loss of AlexNet, ResNet-18, and GoogleNet for Young's modulus classification.

As shown in Fig. 3, the training loss curves further support these results, with ResNet-18 showing the fastest and most stable convergence, followed by AlexNet and GoogleNet. This trend is consistent with their relative performance metrics and highlights the efficiency of ResNet-18 in capturing meaningful signal features.

4. CONCLUSION

In this study, we proposed a deep learning-based NDE method utilizing HNSWs to classify Young's moduli of porous materials. ResNet-18 showed the best performance with an accuracy of 95.56%, followed by AlexNet and GoogleNet. These results confirm the feasibility of combining HNSW-based sensing with deep learning models for accurate and automated material characterization. Future work will explore continuous property estimation through regression and extend the approach to more complex material systems.

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